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Extreme spillover effect of COVID-19 pandemic-related news and cryptocurrencies on green bond markets: A quantile connectedness analysis

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ABSTRACT

We provide the first empirical study on the role of panic and stress related to the COVID-19 pandemic, including six uncertainties and the four most traded cryptocurrencies, on three green bond market volatilities. Based on daily data covering the period from January 1, 2020 to January 31, 2022, we combine Diebold and Yilmaz's (2012, 2014) time domain spillover approach and Ando et al.'s (2022) quantile regression framework to investigate the time-frequency spillover connectedness among markets and measure the direction and intensity of the net transmission effect under extreme negative and positive event conditions, and normal states. We further provide novel insights into the green finance literature by examining sensitivity to quantile analysis of the net transfer mechanism between green bonds, cryptocurrencies, and pandemic uncertainty. Regarding the network connectedness analysis, the results reveal strong net information spillover transmission among markets under the bearish market. In extremely negative event circumstances, the MSCI Euro green bond acts as the leading net shock receiver in the system, whereas COVID-19 fake news appears as the largest net shock contributor, followed by BTC. According to sensitivity to quantile analysis, the net dynamic shock transfer mechanism is time-varying and quantile-dependent. Overall, our work uncovers crucial implications for investors and policymakers.

1. Introduction

During recent periods, global challenges on climate issues have increasingly diversified investors' attention toward newer and emerging financial instruments that may augment sustainable development. One of these newer financial instruments is the emergence of green bonds that address environmental challenges. Wide-ranging literature has deliberated on the major drivers of green bond markets (e.g., [Flammer, 2021](#); [Kamal & Hassan, 2022](#)). A nascent body of literature has explored the underlying nexus between green bonds and major emerging markets. The diversification benefits of green bonds vary across assets and are popularly demonstrated during turbulent conditions of the market, such as the recent pandemic COVID-19 crisis ([Elsayed, Naifar, Nasreen, & Tiwari, 2022](#); [Kamal & Hassan, 2022](#); [Khalfaoui, Jabeur, & Dogan, 2022](#)).

Given that green investments are crucial in alleviating climate change risk and providing a means to achieve risk mitigation, examining

the co-movement between green bonds and financial markets during different market conditions is essential. Accordingly, few scholars notice cryptocurrency market can add to the diversification of the portfolio in conjunction with green bonds to minimize risks, particularly during the recent COVID-19 pandemic ([Kamal & Hassan, 2022](#); [Khalfaoui et al., 2022](#); [Le, Abakah, & Tiwari, 2021](#)). However, these studies, as abundant as studies on the impact of COVID-19 on financial markets and commodities, have ignored the pandemic media coverage influence, given that COVID-19 has received much attention from the media worldwide. Contextualizing this debate, this study examines the connectedness among green bonds, cryptocurrencies, and information spillovers from pandemic-related news during the COVID-19 turmoil. These inter-linkages may affect the sustainable development conditions and the financial performance of green bonds' markets.

Our research has two main objectives. First, it aims to examine the co-movement between green bonds and cryptocurrency markets. To this end, it explores the connectedness between both markets at different

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Table 1
Variables' definitions.

Variable	Ticker	Description
Bloomberg MSCI Global Green Bond Index	GBGLTRUU	The Global MSCI Green Bond Index is a multi-currency benchmark that includes local currency debt markets tracked by the Bloomberg Barclays Global Aggregate Index. Source: Bloomberg
Bloomberg MSCI Euro Green Bond Index	GBEUTREU	This Index offers investors an objective and robust measure of the market for fixed income securities issued in euro, to fund projects with direct environmental benefits. Source: Bloomberg
S&P Green Bond U.S. Dollar Select Index	SPGRUSST	The S&P Green Bond U.S. Dollar Select Index is designed to measure the performance of U.S. dollar-denominated, green-labeled bonds from the S&P Green Bond Index. Source: Bloomberg
Bitcoin	BTC	Current exchange rate Bitcoin to US DOLLAR Source: Bloomberg
Ethereum	ETH	Current exchange rate Ethereum to US DOLLAR Source: Bloomberg
Ripple	RP	Current exchange rate Ripple to US DOLLAR Source: Bloomberg
Litecoin	LTC	Current exchange rate Litecoin to US DOLLAR Source: Bloomberg
Coronavirus Panic Index	PANIC	It measures the level of news chatter that makes reference to panic or hysteria alongside the Coronavirus. Values are from 0 and 100. The higher the index value, the more references to panic found in the media. Source: RavenPack - COVID-19 Global News Monitor.
Coronavirus Media Hype Index	MEDIA_HYPE	The Coronavirus Hype Index measures the percentage of news talking about the novel Coronavirus. Values are from 0 and 100. Source: RavenPack - COVID-19 Global News Monitor
Coronavirus Fake News Index	FAKE_NEWS	The Coronavirus Fake News Index measures the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19. Values range between 0 and 100 where a value of 2.00 indicates that 2% of all news globally is talking about fake news and COVID-19. The higher the index value, the more references to fake news found in the media Source: RavenPack - COVID-19 Global News Monitor
Global Sentiment	SENTIMENT	The Coronavirus Sentiment Index measures the level of sentiment across all entities mentioned in the news alongside the Coronavirus. Source: RavenPack - COVID-19 Global News Monitor
Coronavirus Infodemic Index	INFODEMIC	The Coronavirus Infodemic Index calculates the percentage of all entities (places, companies, organizations, etc.) that are reported in the media alongside COVID-19. Source: RavenPack - COVID-19 Global News Monitor
Coronavirus Media Coverage Index	MEDIA_COVERAGE	The Coronavirus Media Coverage Index calculates the percentage of all news sources covering the topic of the novel Coronavirus. Source: RavenPack - COVID-19 Global News Monitor

quantiles and different frequency domains. Second, it aims to investigate the impact of COVID-19 on the quantile relations of green bonds and other assets by applying media coverage as a COVID-19 proxy. Indeed, COVID-19 was an unprecedented global crisis originating as a health disaster and ultimately transmuted into a major economic disaster. The governments of different countries adopted various strategies to combat the crisis. It is expected that the initial phase of combating the crisis through lock-down measures and social-distancing strictures created panic among investors, which may have created high volatility in the financial markets. Later, the governments of major nations announced economic support programs to overcome the crisis. Such announcements prompted optimism in the markets and may have lowered volatility transmission. These varying conditions are expected to affect green bonds and their specific co-movements.

Using media news data from RavenPack, we consider various types of COVID-19 news-related indices. Concerning green bond markets, we utilize three major green bond indices: the Bloomberg MSCI Global Green Bond Index, Bloomberg MSCI Euro Green Bond Index, and the S&P Green Bond U.S. Dollar Select Index. These indices capture the behavior of the U.S. and European green bond markets, apart from the global performance of green bonds. Further, we capture the information nexus with cryptocurrency by using four major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (RP), and Litecoin (LTC). We explore the interconnectedness between green bonds, cryptocurrencies, and COVID-19 pandemic-related news in both time and frequency domains. In this context, we utilize the spillover methods by [Diebold and Yilmaz \(2012, 2014\)](#). We also analyze asymmetric causality by applying [Ando, Greenwood-Nimmo, and Shin's \(2022\)](#) method, which enables the exploration of risk transmission under different market conditions.

This study offers four contributions to the literature. First, to the best of our knowledge, this is the first study to explore the impact of COVID-19 shocks through pandemic news and the information index on cryptocurrencies and green bond markets. Indeed, given sufficient evidence of media coverage effects on the stock market ([Dang, Dang, Hoang, Nguyen, & Phan, 2020](#); [Liang, Sun, Li, & Yu, 2021](#); [Umar, Adekoya, Oliyide, & Gubareva, 2021](#)), it is important to investigate these effects on two important assets: cryptocurrency and green bonds. Second, as some scholars indicate that there is heterogeneity between different media coverage types (see, e.g., [Atri, Kouki, & imen Gallali, M., 2021](#); [Cepoi, 2020](#)), we use various types of COVID-19 news-related indices to fully understand the role of panic and stress related to COVID-19 media coverage on the volatility of cryptocurrencies and green bond markets. We consider six different COVID-19 news-related indices: four of them have been highlighted by [Zhang, Hong, Guo, and Yang \(2022\)](#) (Coronavirus Panic Emotion Index, Media Hype Index, Fake News Index, Sentiment Index), and two are new indices (Coronavirus Infodemic Index and Coronavirus Media Coverage Index). Third, unlike the earlier literature on green bonds and related markets, we examine asymmetric connectedness by exploring tail risks. Such information would be helpful to investors when financial investments are intricately related to other non-financial risks, such as climate risks and health risks (as evident from the current pandemic) ([Naeem, Farid, Ferrer, & Shahzad, 2021](#)). We explore tail-end risk transmission based on quantile-based estimation methodology, in line with [Pham, Huynh, and Hanif's \(2021\)](#) and [Naeem et al.'s \(2021\)](#) studies. In addition to the interconnectedness of green bonds in the time domain, we further explore the connectedness between green bonds and cryptocurrency at different frequency intervals. The logical connection behind this approach is that connectedness across green bonds with other markets may vary at different frequencies or under differentiated market conditions ([Reboredo & Ugolini, 2020](#)). Similar to [Naeem et al. \(2021\)](#), we utilize the spillover methods postulated by [Diebold and Yilmaz \(2012\)](#) to reveal the connectedness between green bonds and cryptocurrencies across different time horizons. We argue that the superiority of the applied methodology in this study lies in its ability to explore spillover dynamics, unlike other methods that do not explore the direction of the

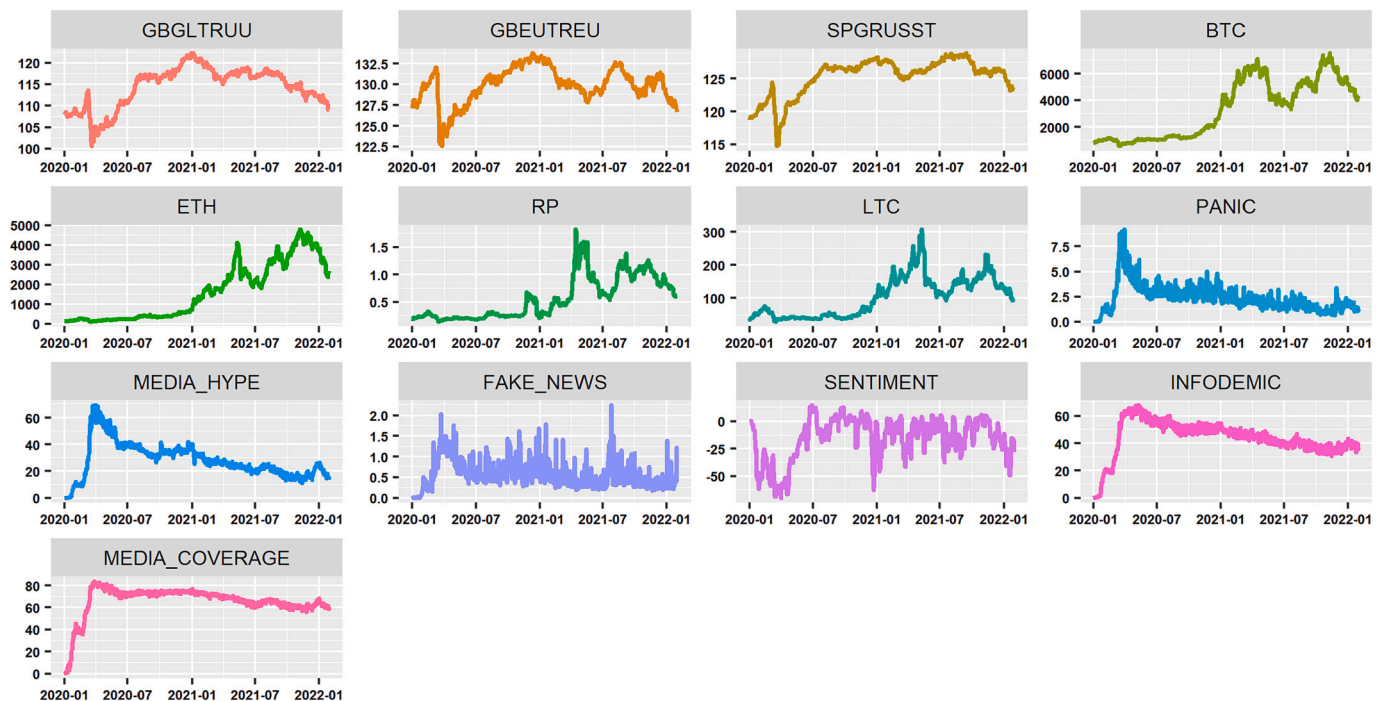


Fig. 1. Dynamic changes of time series.

underlying interconnectedness. Further, to explore the asymmetric causality nexus, we apply the method by [Ando et al. \(2022\)](#) to explore the direction of risk transmission under different market conditions. Herein lies the novelty of the methodological contribution to the existing seam of empirical literature and constitutes the fourth contribution of our study. We contend that the implications of the various risk spillovers from the different pandemic-related indices will affect green bonds and other assets, both in extremely high and low volatility conditions of the market.

Our results describe interesting findings. At the overall level, the static spillover effects are stronger at the extreme upper and lower quantiles than at the middle quantile. Furthermore, the green bond and cryptocurrencies are affected by the uncertainty related to the COVID-19 pandemic. The findings indicate that coronavirus pandemic uncertainty is the biggest contributor to the green bonds and cryptocurrencies markets. Further, there exists a complex pattern of net connectedness across markets in bearish and bullish situations. Under dynamic connectedness, volatility changes in cryptocurrencies affect the future volatility of green bonds in all market situations and periods. Again, the frequency domain Granger causality test indicates that there are pronounced causality effects running from the COVID-19 pandemic to the green bond markets during the short-term business cycle.

The remainder of the paper is organized as follows. The subsequent section reviews recent literature on green bonds and related assets. [Section 2](#) provides the literature review. [Section 3](#) explains the methodology and presents the data sets and descriptive analysis. The major empirical discussion is presented in [Section 4](#). The robustness exercise of the underlying specifications in the empirical exercise is presented in [Section 5](#). The last section presents the conclusion of the study.

2. Literature review

In the recent decade, a wide range of literature has explored the importance of green bonds ([Cepni, Demirer, & Rognone, 2022](#); [Elsayed et al., 2022](#); [Han & Li, 2022](#)). The growing importance of research on green bonds in the extant literature can be contextualized into two edifices. First, against the backdrop of climate change concerns, green bonds are increasingly identified as a source of sustainable finance to

transform the energy trajectory from dirty energy to clean and green energy sources ([Flammer, 2021](#); [Kamal & Hassan, 2022](#); [Sartzetakis, 2021](#)). Second, a major strand of the literature has explored the suitable characteristics of green bonds for portfolio diversification during times of market turbulence ([Kamal & Hassan, 2022](#); [Naeem et al., 2021](#); [Reboredo & Ugolini, 2020](#)). Green bonds are increasingly explored at the backdrop of sustainability on their risk-spillover or risk-receiving attributes in conjunction with related markets. The emergence of green bonds has created concerns among environmental experts, investors, and researchers to explore suitable portfolio diversification properties between green bonds and other assets.

Against the backdrop of the recent crisis, the optimal risk-return trading off in financial markets needs a comprehensive understanding, specifically of the dynamics of co-movements and market interrelations in a portfolio. However, the explorations of the effects of the recent pandemic COVID-19 on green bond markets continue to be scant in the literature ([Elsayed et al., 2022](#); [Naeem et al., 2021](#)). From the perspective of portfolio diversification, the current study delves into the following three aspects: (a) the importance of green bonds and market interlinkages; (b) the importance of cryptocurrencies, green bonds, and hedging effectiveness; (c) the current pandemic crisis and fragility across financial markets; and (d) media coverage and financial markets. [Table A1](#) provides a summary overview of these studies.

2.1. Green bond markets

A major strand in the literature has focused discussions in recent periods on green stocks and bonds, particularly in the backdrop of concerns about climate change ([Arif, Naeem, Farid, Nepal, & Jamasb, 2021](#); [Kuang, 2021](#); [Tolliver, Keeley, & Managi, 2020](#); [Yousaf, Suleman, & Demirer, 2022](#)). Recently, [Han and Li \(2022\)](#) explored the asset allocation properties of green bonds using copula-based methods. The study concluded that the beneficial impacts of green bonds in portfolio management come during an increase in returns and a decline in market volatility. Similarly, [Cepni et al. \(2022\)](#) deliberated on the hedging properties of green assets and other precious metals against climate uncertainty. The findings of this study suggest that green bonds can be an effective instrument for managing climate risks in investment

Table 2
Summary statistics.

	GBGLTRUU	GBEUTREU	SPGRUSST	BTC	ETH	RP	LTC	PANIC	MEDIA_HYPE	FAKE_NEWS	SENTIMENT	INFODEMIC	MEDIA_COVERAGE
Mean	-0.001	0.000	-0.006	-4.62	-3.35	-0.001	-0.079	-0.001	-0.021	-0.002	0.031	-0.049	-0.079
Variance	0.142	0.076	0.046	15.828532	8217.357	0.002	42.304	0.36	4.327	0.078	21.399	5.582	2.899
Skewness	1.265***	1.171***	1.949***	0.458***	2.155***	0.891***	2.757***	0.539***	0.262***	-0.147*	0.142	0.156*	0.003
Kurtosis	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.003	-0.096	-0.107	-0.078	-0.976
	13.796***	12.299***	19.374***	4.081***	18.923***	36.945***	34.359***	3.958***	5.491***	6.093***	2.567***	0.972***	2.157***
JB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	6238.056***	4970.081***	12.383.475***	554.840***	11.943.326***	43.381.474***	38.397.055***	533.571***	964.702***	1179.880***	211.452***	33.063***	147.575***
ERS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-8.984***	-3.233***	-6.104***	-9.449***	-12.055***	-11.328***	-10.113***	-23.201***	-17.266***	-19.826***	-11.672***	-26.541***	-13.957***
Q(10)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	70.014***	40.127***	146.150***	13.772**	26.745***	17.416***	28.710***	102.558***	114.318***	129.838***	137.373***	262.819***	64.940***
Q2(10)	0.000	0.000	0.000	-0.011	0.000	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	171.883***	193.731***	489.138***	112.598***	85.223***	27.702***	41.190***	77.203***	228.660***	108.385***	42.294***	165.678***	76.161***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

portfolio management.

There is ample evidence that green bonds can be an important instrument for portfolio diversification (Broadstock & Cheng, 2019; Mzoughi, Urom, & Guesmi, 2022; Naeem et al., 2021). Broadstock and Cheng (2019) reported that the relevance of green bonds and other conventional bonds is intricately dependent on the financial conditions of the market. Nguyen, Naeem, Balli, Balli, and Vo (2021) found that the association between green bonds and other bonds is time-varying. The study demonstrated robust co-movements with clean energy stocks. The recent study by Mzoughi et al. (2022) and Elsayed et al. (2022), in conformity with earlier studies, showed that green bonds display significant co-movements with other markets, particularly during times of market turbulence. These findings suggest that investors can use green bonds to manage risks in the portfolio structure.

2.2. Importance of cryptocurrencies, and market co-movements with green bonds

During the recent decade, widespread research has discussed the importance of cryptocurrencies as a safe-haven asset and having an important hedging role amid uncertainties, particularly during the recent pandemic (Akhtaruzzaman, Boubaker, & Sensoy, 2021; Bariviera & Merediz-Solà, 2021; Bouri, Gupta, Tiwari, & Roubaud, 2017; Conlon, Corbet, & McGee, 2020; Corbet, Lucey, Urquhart, & Yarovaya, 2019; Guesmi, Saadi, Abid, & Ftiti, 2019; Urquhart & Zhang, 2019; Wu, Tong, Yang, & Derbali, 2019). Alternatively, some studies have found a higher incidence of the volatility of cryptocurrencies in comparison to conventional assets (Corbet, Larkin, Lucey, & Yarovaya, 2020; Dwyer, 2015).

Unarguably, a relatively young strand in the current literature has discussed the underlying association between green bonds and cryptocurrencies. Naeem and Karim (2021) reported that green bonds have hedging properties against BTC. The empirical findings by Le et al. (2021) show that time and frequency domain connectedness and spillover are among Fintech, green bonds, and cryptocurrencies. Using a TVP-VAR network connectedness model, Pham et al. (2021) found that the spillovers among cryptocurrency, green, and fossil fuel assets vary over time and are more pronounced during crisis periods. Further, the spillovers among these assets are asymmetric, with negative return spillovers being larger than positive return spillovers. Kamal and Hassan's (2022) study highlights the properties of cryptocurrencies as asset diversifiers alongside the performance of green bonds. However, in bullish market conditions, green bonds fail to show a positive association with cryptocurrencies. During the pandemic period, the study showed high levels of contagion behavior across the markets.

The aforementioned discussion shows that a growing body of research has deliberated on the importance of cryptocurrencies as important financial instruments. The research described the high volatility nature of cryptocurrency markets. There is mixed evidence of the relationship between cryptocurrency and other assets.

2.3. COVID-19: Fragility in the financial market

The recent pandemic COVID-19 was associated with the significant fragile nature of global financial markets. Against this backdrop, previous studies (Akhtaruzzaman et al., 2021; Guo & Zhou, 2021; Wan, Xue, Linnenluecke, Tian, & Shan, 2021; Yousaf et al., 2022) have explored the hedging effectiveness of green bonds during the crisis period in particular. Guo and Zhou (2021) found that the hedging effectiveness of green bonds is asymmetric during periods of market turbulence. Recently, Tiwari, Abakah, Gabauer, and Dwumfour (2022), using daily frequency-based observations from January 2015 to September 2020, explored the interconnectedness of green bonds, carbon prices, and stocks on renewable energy. Based on numerous portfolio techniques, the findings demonstrated that clean energy was the dominant source of the net transmitter of shocks, whereas green bonds

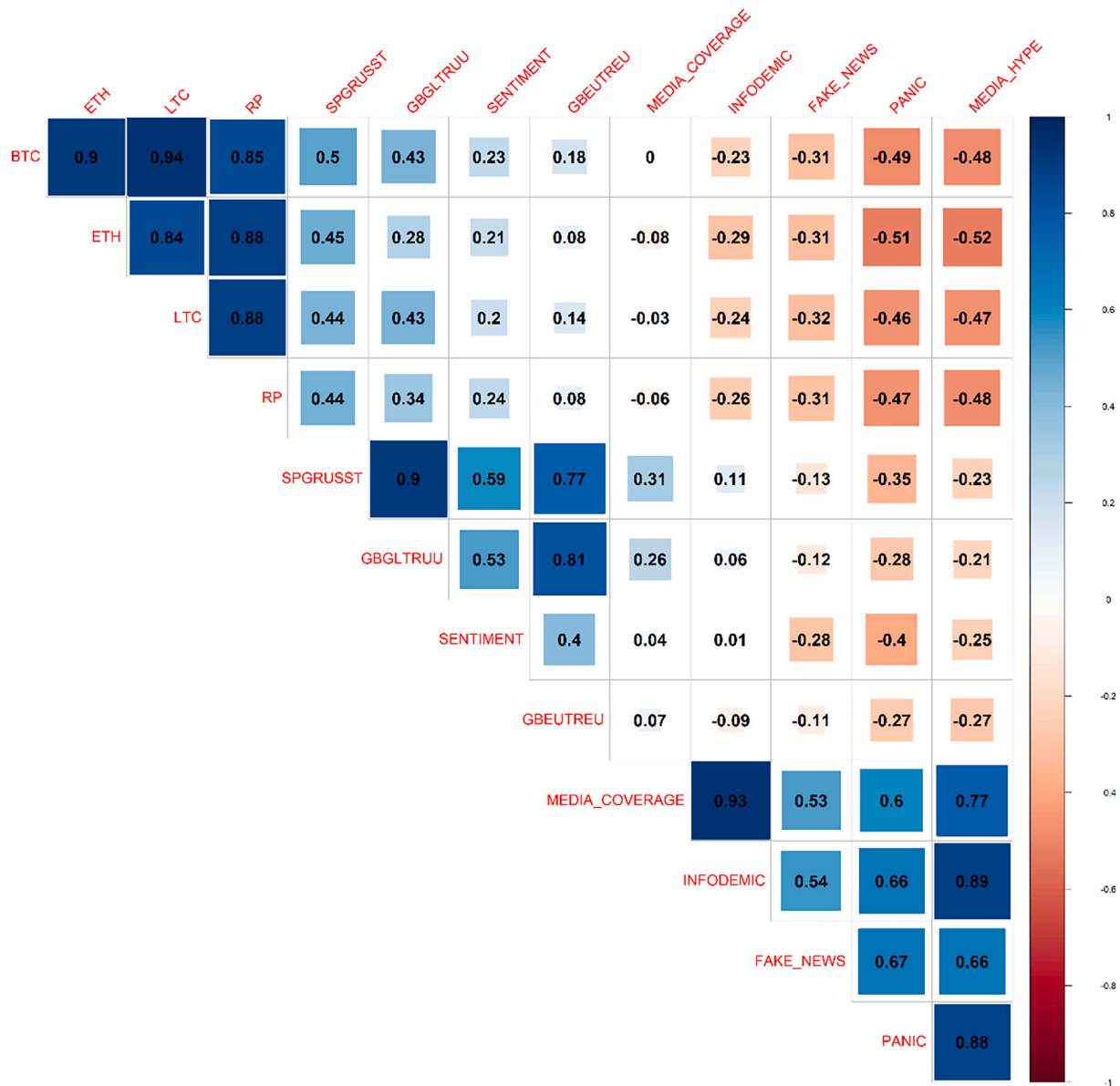


Fig. 2. Heatmap correlation between market pairs.

appeared as the major recipients of shocks in the portfolio. The same pattern was evident during the time of pandemic COVID-19.

2.4. Media coverage and financial markets

Klibanoff, Lamont, and Wizman (1998) and Tetlock (2007) argued that important media pessimism leads to downward pressure on market prices, as pessimistic news affects investor sentiment. Wu and Lin's (2017) empirical results show that both the positive and negative tone of media coverage justify abnormal returns. Dang et al. (2020) indicated that media coverage is negatively correlated with stock price synchronization. Some researchers have focused on the impact of COVID-19-related news on financial markets. For example, Baig, Butt, Haroon, and Rizvi (2021) found that COVID-19-related news negatively impacts negative investors and deteriorates stock market liquidity and stability. Atri et al. (2021) determined that COVID-19 media coverage has positive effects on the dynamics of oil and gold prices. Sarkodie, Ahmed, and Owusu (2022) showed that news on COVID-19 confirmed cases and deaths have a significant impact on the market prices of BTC, Bitcoin Cash, ETH, and LTC. Bouteska, Mefteh-Wali, and Dang (2022)

investigated whether COVID-19 had an impact on investor behavior, leading to the presence of over- or underreaction on the price of BTC. They concluded that during the COVID-19 pandemic, investors' sentiments had a significant impact on BTC returns.

A nascent literature indicates that different media report types have heterogeneous impacts on investors' sentiments and then on financial markets. Using data from the top six countries most affected by the pandemic, Cepoi (2020) reported that stock markets present asymmetric dependencies with COVID-19-related information, such as fake news, media coverage, or contagion. This conclusion highlights the need to use proper communication channels to mitigate COVID-19-related financial turmoil. Haroon and Rizvi (2020) demonstrated that the overwhelming panic generated by news outlets is associated with increasing volatility in equity markets around the world. However, sentiment and the quantum of media coverage had little to moderate association with price volatility. Zhang et al. (2022) explored information spillover from different types of COVID-19 news-related indices to crude oil, gold, and BTC markets. They found that both the return and volatility spillovers from COVID-19 news were stronger in the short term. Further, panic sentiment and media hype significantly affect the BTC market. Panic

Table 3
Static connectedness under bearish market (extreme lower quantile: $\tau = 0.05$).

	GBGLTRUU	GBEUTREU	SPGRUSST	BTC	ETH	RP	LTC	PANIC	MEDIA_HYPE	FAKE_NEWS	SENTIMENT	INFODEMIC	MEDIA_COVERAGE	FROM others
GBGLTRUU	16.71	8.67	9.32	7.01	7.67	7.02	7.18	6	5.66	6.4	6.13	5.66	6.56	83.29
GBEUTREU	8.48	17.04	10.85	7.11	6.63	6.7	7.05	6.02	5.71	6.12	6.05	5.83	6.43	82.96
SPGRUSST	7.51	9.61	18.47	6.95	6.77	6.79	7.26	6.22	5.93	5.85	6.62	5.5	6.52	81.53
BTC	5.85	7.03	7.44	15.13	9.72	9.05	9.96	5.65	5.75	5.91	6.41	5.74	6.36	84.87
ETH	6.01	7.48	7.55	9.23	14.6	10.34	10.59	5.36	5.69	6.06	5.77	5.31	6.01	85.4
RP	5.88	7.16	6.98	8.18	9.94	16.78	10.25	5.01	5.8	5.56	6.41	5.67	6.38	83.22
LTC	5.64	7.53	8.05	9.94	10.07	10.38	13.7	5.46	5.7	5.73	6.33	5.37	6.12	86.3
PANIC	6.84	6.57	7.49	6.09	6.36	5.97	6.23	18.37	7.19	7.47	6.72	7.12	7.59	81.63
MEDIA_HYPE	6.6	6.07	6.76	7.12	7.35	7.51	6.72	7.3	17.01	6.49	6.82	6.47	7.78	82.99
FAKE_NEWS	6.77	7.36	7.11	7.89	6.73	7.17	6.95	6.24	6.49	18.28	7.28	5.36	6.36	81.72
SENTIMENT	6.54	6.52	7.54	7.42	6.94	7.37	7.55	5.43	6.41	6.37	18.91	5.74	7.26	81.09
INFODEMIC	6.42	6.9	6.8	6.55	6.96	7.05	6.96	5.35	6.82	6.11	6.41	18.78	8.89	81.22
MEDIA_COVERAGE	6.53	7	7.52	7.04	6.69	7.58	6.74	6.39	6.6	6.56	7.68	7.38	16.27	83.73
TO others	79.07	87.89	93.42	90.53	91.83	92.93	93.45	70.45	73.75	74.62	78.62	71.13	82.26	1079.95
Inc. own	95.78	104.92	111.89	105.66	106.43	109.72	107.15	88.82	90.75	92.9	97.53	89.91	98.53	
NET	-4.22	4.92	11.89	5.66	6.43	9.72	7.15	-11.18	-9.25	-7.1	-2.47	-10.09	-1.47	
NPDC	7	2	0	4	4	2	3	11	10	9	7	11	8	TCl = 83.07%

Note: This table reports the findings of the causal effects for the return spillovers extracted from QVAR based on 10-step-ahead forecast and 100-days rolling-window. The column "FROM" designates the spillover effects taken by a particular index from all other indexes. The row "TO" shows the total spillover given by a particular index to all other indexes. The row "NET" defines whether a particular index is a net receiver (negative value) or net contributor (positive value) of spillovers.

Table 4
Static connectedness under normal market (intermediate quantile: $\tau = 0.50$).

	GBGLTRUU	GBEUTREU	SPGRUSST	BTC	ETH	RP	LTC	PANIC	MEDIA_HYPE	FAKE_NEWS	SENTIMENT	INFODEMIC	MEDIA_COVERAGE	FROM others
GBGLTRUU	45.25	8.25	9.32	4.94	4.41	4.36	4.68	3.31	3.29	3.25	2.95	2.65	3.35	54.75
GBEUTREU	9.1	41.58	11.93	4.05	5.61	4.98	4.75	3.15	3.1	2.94	2.73	3.03	3.04	58.42
SPGRUSST	8.24	10.75	43.55	4.79	4.57	4.3	4.56	4.03	3.04	3.06	3.14	2.49	3.49	56.45
BTC	4.35	3.06	3.79	34.99	13.27	10.23	14.16	2.79	3.31	2.69	2.96	2.22	2.18	65.01
ETH	3.32	2.68	2.63	12.43	36.54	13.1	16.49	2.22	2.03	1.76	2.42	2.08	2.31	63.46
RP	2.73	2.25	2.7	8.8	13.59	42.73	14.98	1.87	2.35	2.04	1.97	1.73	2.24	57.27
LTC	3.08	2.36	2.5	13.83	17.07	15.9	33.56	1.84	2.04	1.81	2.24	1.85	1.92	66.44
PANIC	4.23	4.34	3.88	4.16	4.5	6.03	5.58	41.74	5.98	6.04	4.48	5.08	3.98	58.26
MEDIA_HYPE	3.82	3.54	4.28	5.01	4.91	5.51	4.13	7.18	45.01	43.47	4.69	4.03	5.81	54.99
FAKE_NEWS	3.51	3.93	5.04	5.62	4.33	6.19	5.48	6.14	4.27	4.37	4.55	3.11	4.21	56.53
SENTIMENT	3.67	3.09	4.7	4.83	4.19	4.98	3.95	3.42	2.68	4.29	54.45	2.71	3.04	45.55
INFODEMIC	3.75	3.9	4.06	4.27	3.72	4.63	4.21	5.19	5.14	3.23	4.12	48.91	4.87	51.09
MEDIA_COVERAGE	6.33	4.33	4.1	4.09	5.09	5.44	5.12	4.02	6.07	3.7	4.63	5.77	41.31	58.69
TO others	56.12	52.47	58.93	76.83	85.28	85.65	88.08	45.16	43.3	38.81	39.08	36.77	40.44	746.91
Inc. own	101.37	94.05	102.48	111.83	121.81	128.38	121.64	86.89	88.31	82.28	93.53	85.68	81.75	
NET	1.37	-5.95	2.48	11.83	21.81	28.38	21.64	-13.11	-11.69	-17.72	-6.47	-14.32	-18.25	
NPDC	5	6	5	3	0	1	2	7	9	11	7	11	11	TCl = 57.45%

Note: see notes in Fig.3.

Table 5
Static connectedness under bullish market (extreme upper quantile: $\tau = 0.95$).

	GBGLTRUU	GBEUTREU	SPGRUSST	BTC	ETH	RP	LTC	PANIC	MEDIA_HYPE	FAKE_NEWS	SENTIMENT	INFODEMIC	MEDIA_COVERAGE	FROM others
GBGLTRUU	17.7	8.15	9.44	7.43	7.13	6.36	7.04	6.56	6.16	7.02	4.96	5.55	6.49	82.3
GBEUTREU	8.46	16.7	9.83	7.43	7.03	6.89	6.68	6.69	6.2	7.06	5.44	5.68	5.92	83.3
SPGRUSST	8.73	8.75	18.59	7	7.09	6.79	6.9	6.46	6.58	6.56	4.96	5.67	5.92	81.41
BTC	6.87	6.31	6.57	16.57	10.71	8.21	9.87	5.65	6.19	6.61	5.25	5.44	5.74	83.43
ETH	6.77	6	5.94	9.9	18.17	8.9	10.63	5.34	6.05	6.31	4.96	5.47	5.55	81.83
RP	6.24	5.56	6.49	8.78	10.76	17.76	9.99	5.98	5.91	6.29	4.79	5.04	6.41	82.24
LTC	6.07	5.6	5.95	10.18	11.77	9.99	16.08	5.96	5.81	6.7	5.02	5.33	5.54	83.92
PANIC	6.63	6.5	7.25	7.31	6.28	5.75	6.76	17.89	7.59	8.08	5.81	7.09	7.07	82.11
MEDIA_HYPE	6.76	6.03	6.7	6.84	7.25	6.34	6.14	9.18	17	7.76	5.5	6.59	7.92	83
FAKE_NEWS	7.89	6.53	7.74	8.04	7.02	6.58	6.76	8.18	6.55	16.62	5.81	6.14	6.13	83.38
SENTIMENT	6.66	6.23	6.65	7.62	7.52	6.91	6.86	6.54	6.33	6.8	20.52	5.71	5.66	79.48
INFODEMIC	6.2	6.16	6.74	7.05	6.89	6.07	6.16	6.57	8.1	7.15	5.23	21.09	6.58	78.91
MEDIA_COVERAGE	6.56	6.4	6.13	6.53	7	6.72	7.34	6.85	7.74	7.16	5.54	7.11	18.93	81.07
TO others	83.82	78.21	85.43	94.09	96.45	85.5	91.13	79.98	79.23	83.5	63.27	70.83	74.94	1066.38
Inc. own	101.52	94.91	104.02	110.66	114.62	103.26	107.2	97.87	96.23	100.12	83.78	91.92	93.87	
NET	1.52	-5.09	4.02	10.66	14.62	3.26	7.2	-2.13	-3.77	0.12	-16.22	-8.08	-6.13	
NPDC	5	9	4	1	0	4	2	7	9	7	12	9	9	TCI = 82.03%

Note: see notes in Fig.3.

sentiment contributes the most to the crude oil market, while media hype acts as the main transmitter in the gold market.

2.5. Earlier gaps and novelty of the current study

As mentioned above, studies on green bonds and their interconnectedness across markets are emerging, but they continue to be scant in several ways. First, given the recent evolution of green bonds as a climate change hedging tool, as well as cryptocurrencies' popularity as portfolio diversifiers, it is important to explore spillovers across cryptocurrency because research in this stream continues to report pieces of mixed evidence (Giudici & Polinesi, 2021; Huynh, Hille, & Nasir, 2020). This gap in the literature represents the first major focus of our study. Second, no studies in the extant literature have explored the asymmetric interconnectedness between green bonds and the cryptocurrency market. It is important to explore asymmetries, because investors react differently to positive and negative shocks emanating in the markets. Thus, we also address this major gap in the literature by exploring the asymmetric interconnectedness of these assets in earlier studies. The third major gap addressed in this study is financial fragility during the pandemic. Through a comprehensive analysis, we add to this limited body of research by using six indicators on COVID-19 uncertainty to explore how media, public attention, fake sentiments, and panic news, among others, may affect green bonds and major aspects of the cryptocurrency market.

3. Methodology and data

3.1. Methodology

To examine the connectedness among global green bond, cryptocurrencies, and uncertainty indexes of COVID-A9 pandemic, we use the multivariate time-series analysis model advanced by Diebold and Yilmaz (2012) and the quantile connectedness approach proposed by Ando et al. (2022). The following sub-sections briefly present these methodologies.

3.1.1. Standard VAR model

The spillover index approach builds on variance decompositions on a p -th order VAR with N -variable, i.e., $\text{VAR}_N(p)$. $\text{VAR}(p)$, $u_t = \sum_{i=1}^p \Phi_i u_{t-i} + c_t$, where $c_t \sim N(0, \Sigma)$. The moving average (MA) representation of this model can be described as $u = \sum_{i=0}^{\infty} B_i c_{t-i}$, where B_i represents $N \times N$ coefficient matrices and it obeys the recursion $B_i = \Phi_1 B_{i-1} + \Phi_2 B_{i-2} + \dots + \Phi_p B_{i-p}$, with B_0 is an $N \times N$ identity matrix and $B_i = 0$ for $i < 0$. Following Diebold and Yilmaz (2012), we utilize the generalized variance decomposition framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), which is invariant to ordering. Thus, we denote each entry of the spillover connectedness table as $\nabla_{ij}^g(H)$, which estimates the contribution of variable j to the H -step-ahead generalized variance of forecast error of variable i and it is computed by:

$$\nabla_{ij}^g(H) = \frac{r_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' B_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h \Sigma B_h' e_i)^2}, H = 1, 2, \dots \quad (1)$$

where Σ is the covariance matrix of errors and σ_{jj} denotes the standard deviation of the disturbance term of j -th equation. e_i is the selection vector with one for i -th component and zeros otherwise. Since the sum of the rows of the generalized variance decomposition matrix is not equal to one (i.e. $\sum_{j=1}^N \nabla_{ij}^g(H) \neq 1$), we normalize each entry of the generalized variance decomposition matrix by the row sum:

$$\tilde{\nabla}_{ij}(H) = \frac{\nabla_{ij}(H)}{\sum_{j=1}^N \nabla_{ij}(H)} \quad (2)$$

Hence, $\sum_{j=1}^N \tilde{\nabla}_{ij}(H) = 1$ and $\sum_{i,j=1}^N \tilde{\nabla}_{ij}(H) = N$.

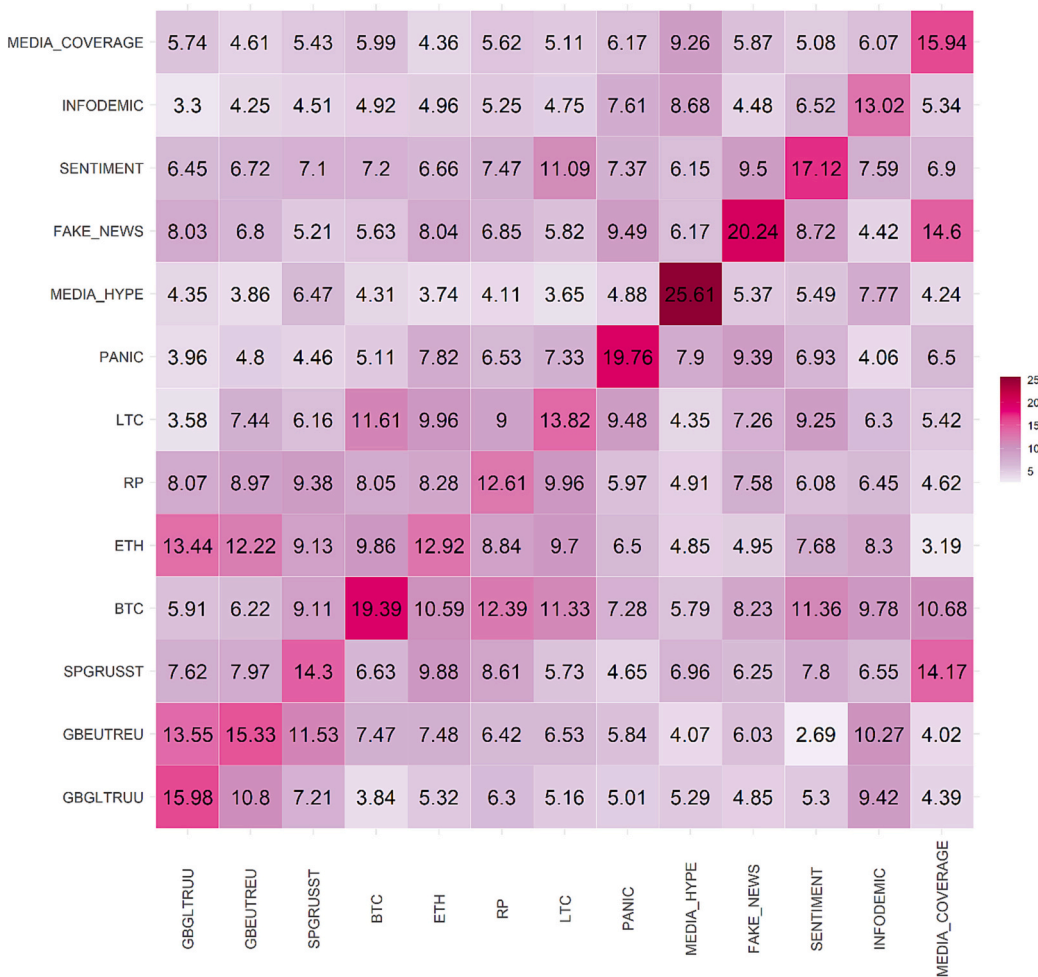


Fig. 3. Heatmap visualization for the static connectedness of volatility spillovers under bearish market (the 5th quantile). Notes: The results are extracted from QVAR model with a lag length of order 1 (Schwarz information criterion) based on a 10-step-ahead generalized forecast error variance decomposition and 100-days rolling-window. The relative intensity of the different colors is depicted in the color bar where darker (lighter) color refers to high (low) connectedness. (We refer the reader to the Web version of this paper for interpretation of the references to color in this figure legend).

For the convenience of notation, let $C_{i \leftarrow j}^H$ denote the pairwise directional connectedness from variable j to variable i and $C_{i \rightarrow j}^H$ refers to the pairwise directional connectedness from variable i to j . These two connectedness measures are defined as follows:

$$C_{i \leftarrow j}^H = \sum_{j=1, i \neq j}^K \tilde{V}_{ij}(H) \quad (3)$$

$$C_{i \rightarrow j}^H = \sum_{j=1, i \neq j}^K \tilde{V}_{ji}(H) \quad (4)$$

Generally, $C_{i \leftarrow j}^H \neq C_{j \leftarrow i}^H$, so we get $N^2 - N$ separate pairwise directional connectedness measures. The net spillover flows from variable i to variable j , is the net pairwise directional connectedness computed as $C_{ij}^H = C_{j \leftarrow i}^H - C_{i \leftarrow j}^H$. For more details about the connectedness measures we refer the readers to (Liu & Gong, 2020; Naeem et al., 2021; Tiwari et al., 2022).

3.1.2. Quantile connectedness measures

We employ the quantile connectedness approach proposed by Ando et al. (2022) to examine the quantile propagation mechanism between variables. To calculate all connectedness metrics, we first estimate a quantile vector autoregression, QVAR(p), which can be written as follows

$$u_t = \delta(\tau) + \sum_{j=1}^p \Phi_j(\tau) u_{t-j} + c_t(\tau) \quad (5)$$

u_t is the vector of $N \times 1$ dimensional endogenous variables, τ stands for quantile of interest which varies between $[0,1]$, p is the lag length, $\delta(\tau)$ is

the $N \times 1$ dimensional mean vector, $\Phi_j(\tau)$ is the $N \times N$ dimensional QVAR coefficient matrix, and $c_t(\tau)$ indicates the error term which has a $N \times N$ dimensional variance-covariance matrix, $\Sigma(\tau)$.

We then use Wold's theorem to transform QVAR(p) to its quantile moving-average representation:

$$u_t = \delta(\tau) + \sum_{j=1}^p \Phi_j(\tau) u_{t-j} + c_t(\tau) = \delta(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) + c_{t-i} \quad (6)$$

Then, we calculate the quantile spillover index from the H-step ahead of Koop et al. (1996) and Pesaran and Shin (1998) which illustrates the impact a shock in variable j has on variable i :

$$\psi_{ij}^s(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} (\epsilon_i' \Psi_h(\tau) \Sigma(\tau) \epsilon_j)^2}{\sum_{h=0}^{H-1} (\epsilon_i' \Psi_h(\tau) \Sigma(\tau) \Psi_h(\tau)' \epsilon_i)} \quad (7)$$

$$\tilde{\psi}_{ij}^s(H) = \frac{\psi_{ij}^s(H)}{\sum_{j=1}^N \psi_{ij}^s(H)} \quad (8)$$

where ϵ_i denotes a zero vector with unity on the i -th position. Before calculating the pairwise connectedness measures at various quantiles, we normalize each entry in the connectedness table as $\sum_{j=1}^N \tilde{\psi}_{ij}^s(H) = 1$ and $\sum_{i,j=1}^N \tilde{\psi}_{ij}^s(H) = N$. Then we get net pairwise connectedness as described in subsection 3.1.1.

3.2. Data and descriptive analysis

In the present study, we examined the dependence structure and connectedness of the green bond market with some cryptocurrencies

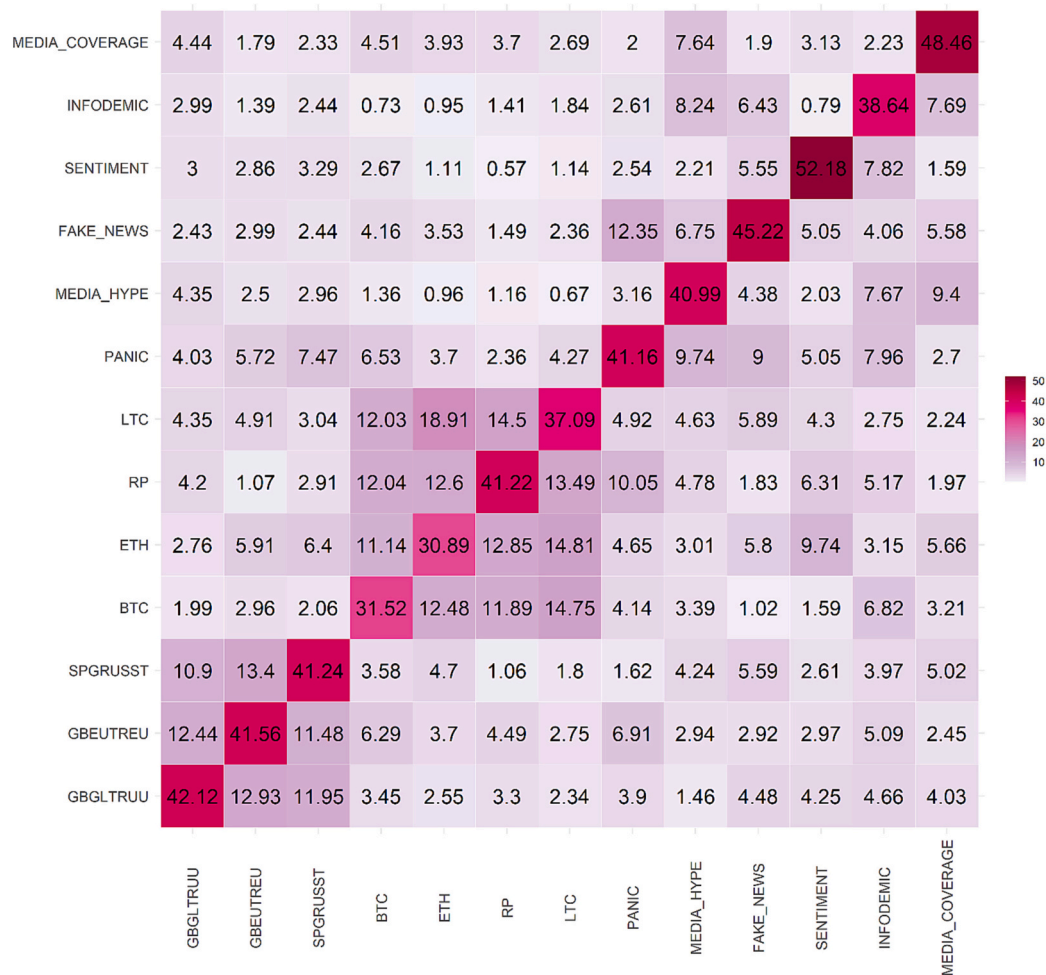


Fig. 4. Heatmap visualization for the static connectedness of volatility spillovers under normal market (the 50th quantile). Notes: refer to notes in Fig. 3.

and uncertainty indexes of the COVID-19 pandemic for the period of January 1, 2020 to January 31, 2022. Three types of global green bond indices were used to measure the financial performance of the green bonds market: Bloomberg MSCI Global Green Bond Index (GBGLTRUU), Bloomberg MSCI Euro Green Bond Index (GBEUTREU), and S&P Green Bond U.S. Dollar Select Index (SPGRUSST). Generally, indexes measure the global market for fixed-income securities issued to fund projects with direct environmental benefits. For cryptocurrencies, we used BTC, ETH, RP, and LTC. The daily series for green bond indexes and cryptocurrencies were obtained from the Bloomberg database.

To examine the impact of COVID-19-related media coverage on green bonds and cryptocurrencies markets, and because the impacts of the different types of news are diverse, we used various types of COVID-19 news-related indexes instead of a single index. We considered six indexes: Coronavirus Panic Index (PANIC), Coronavirus Media Hype Index (MEDIA_HYPE), Coronavirus Fake News Index (FAKE_NEWS), Global Sentiment (SENTIMENT), Coronavirus Infodemic Index (INFODEMIC), and Coronavirus Media Coverage Index (MEDIA_COVERAGE). All the series related to the COVID-19 pandemic are sourced from RavenPack, which proposes *The Coronavirus Media Monitor* (coronavirus.ravenpack.com), a live and interactive website that tracks the latest information on the novel Coronavirus in the media worldwide, such as Dow Jones Newswire and StockTwits, in order to identify key trends and patterns emerging from the news.

The return series were calculated using the first difference form. Table 1 presents a description of the different variables used in this study. The indices from RavenPack have been used by some researchers to investigate the impacts of COVID-19 on financial markets (Cepoi,

2020; Zhang et al., 2022) and this current study is the first to use them in order to examine spillover of COVID-19-related information to green bond markets. Further, we included more indexes than those in previous studies to deal with heterogeneity in news data.

Fig. 1 displays the dynamics of the three green bond indices, the four cryptocurrencies, and the six COVID-19 pandemic indexes. We observed that all the series were not stationary. We noted sharp breaks in all series throughout the period. There were sections of time when there was a high level of volatility and periods of time when volatility was moderately low, which depicts an apparent volatility clustering in some periods. Furthermore, we noticed that the COVID-19 pandemic-related index values had severe volatility during 2020. Interestingly, the prices of green bond indexes closely co-moved and exhibited severe volatility during 2020. This is unlike the prices of the four cryptocurrencies, which showed moderately fluctuating trends throughout 2020. Similar temporal patterns were detected for the four cryptocurrencies.

Table 2 presents the summary statistics of the daily returns. Focusing on the mean returns, we noted that the daily mean was positive for all series except SENTIMENT. The highest volatile variables were BTC, followed by ETH. Green bond indexes were less volatile than cryptocurrencies (except RP), as their standard deviation were lower than those of BTC, ETH, and LTC. We also observed that all market returns were leptokurtic. The kurtosis, skewness, and Jarque–Bera measures indicated non-normal price distributions for all markets. Further, the ERS statistics rejected the null hypothesis for the unit root at the 1% level. In addition, as shown in Table 1, all the series except SENTIMENT, INFODEMIC, and MEDIA_COVERAGE recorded kurtosis exceeding threshold 3, which surmises that the returns series for the period had

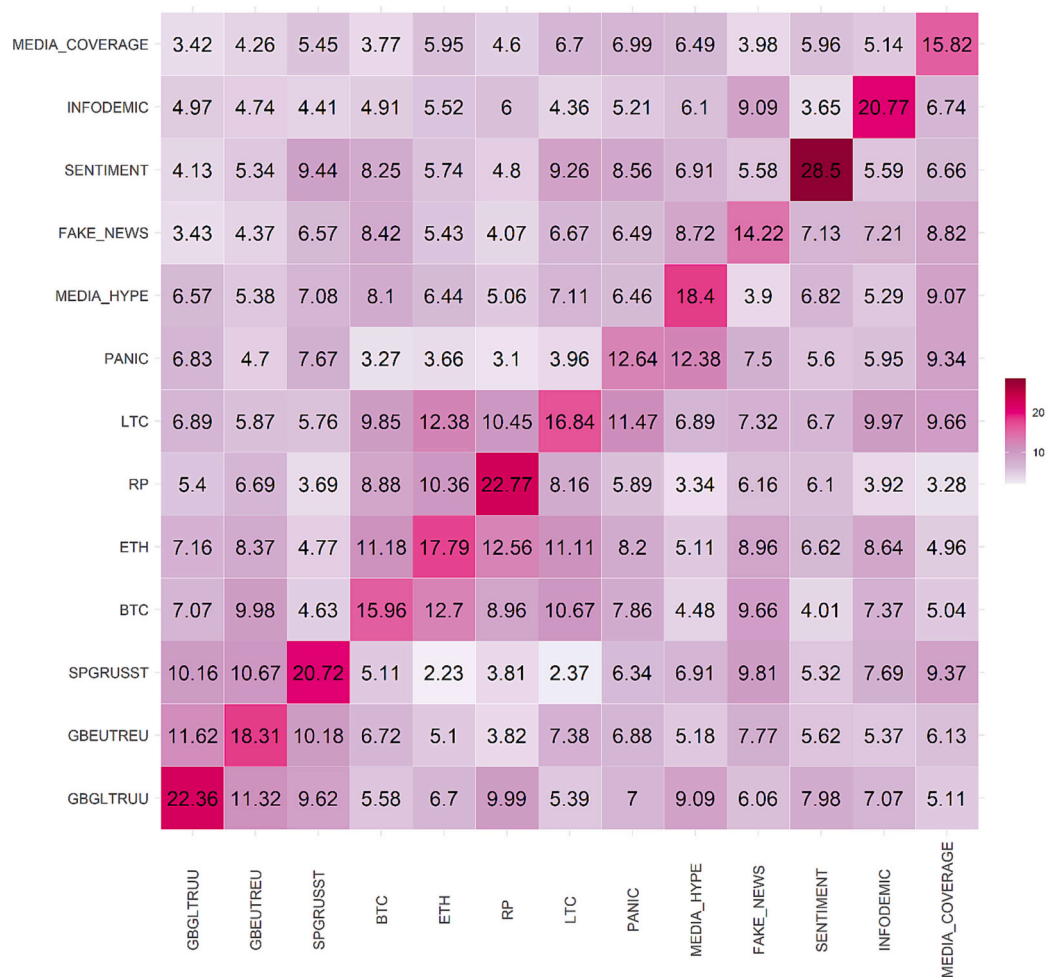


Fig. 5. Heatmap visualization for the static connectedness of volatility spillovers under bullish market (the 95th quantile). Notes: refer to notes in Fig. 3.

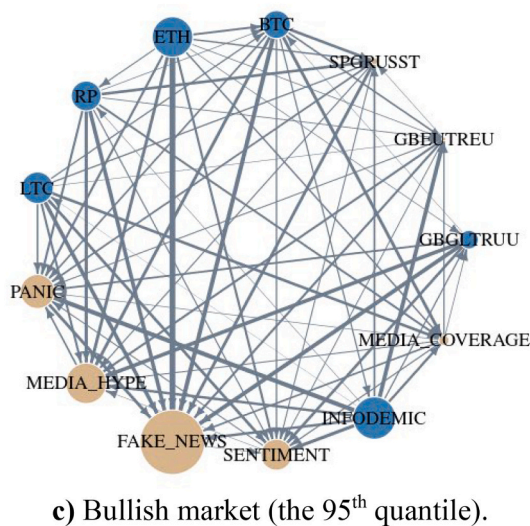
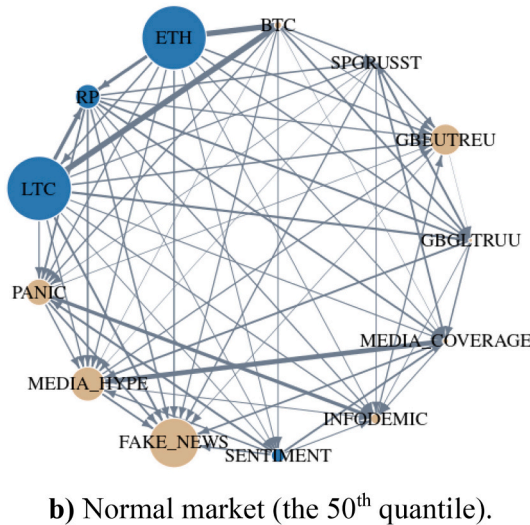
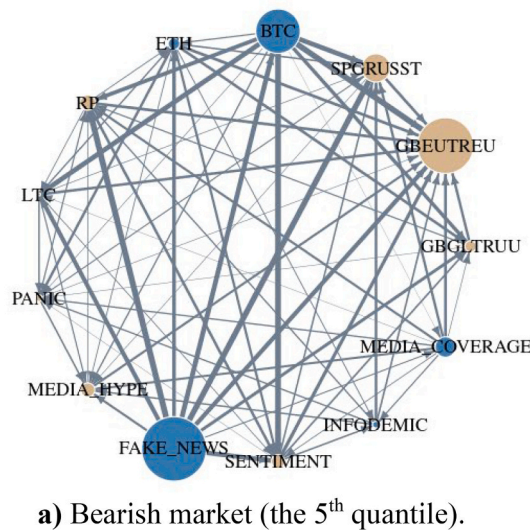
flatter tails compared to what would be anticipated from a normally distributed series. Further, Jarque–Bera allows us to reject the null hypothesis of normality for all series at the 1% level, and the ERS statistics argue the reject of the null hypothesis for the unit root at the 1% level.

Fig. 2 shows the correlation matrix between each variable using heatmap representations for the full sample period. A dark red color indicates an extremely negative correlation between two variables, while dark blue indicates an extremely positive correlation. For instance, the three indices related to the COVID-19 pandemic (FAKE_NEWS, PANIC, and MEDIA_HYPE) were significantly and negatively correlated with cryptocurrencies and green bond indices. This may be attributed to higher media coverage during the pandemic period, leading to negative sentiments that caused markets to decline and volatility to rise. A result of greater interest is that each cryptocurrency had a positive correlation with each green bond index. However, this correlation was relatively moderate, which suggests that cryptocurrencies could be used as diversifiers. A diversifier is an asset that has a weak positive correlation with another asset on average (Baur & Lucey, 2010).

4. Findings and discussion

4.1. Static quantile spillover connectedness

Before running the process estimation of the VAR models, we selected an optimal lag length of order 1 based on the Schwarz information criterion for the VAR(p) model. We set the forecast cycle step to 10 days to estimate volatility connectedness. To capture the dynamic total and directional spillover connectedness, we employed a rolling window analysis of a width of 100 days. Tables 3–5 depict the estimates of the variance decomposition matrix and the different spillover measures. In each table, the ij th component is the forecast variance contribution to variable i from variable j . The directional spillovers “From others” are shown in the off-diagonal row sums, while the directional spillovers “TO others” are displayed in the off-diagonal column sums. The “NET” spillovers depicted at the bottom of each table are calculated as “TO others” minus “FROM others.” The TCI indicates the total spillovers, which is the average of spillovers “FROM others” (or “TO others”).



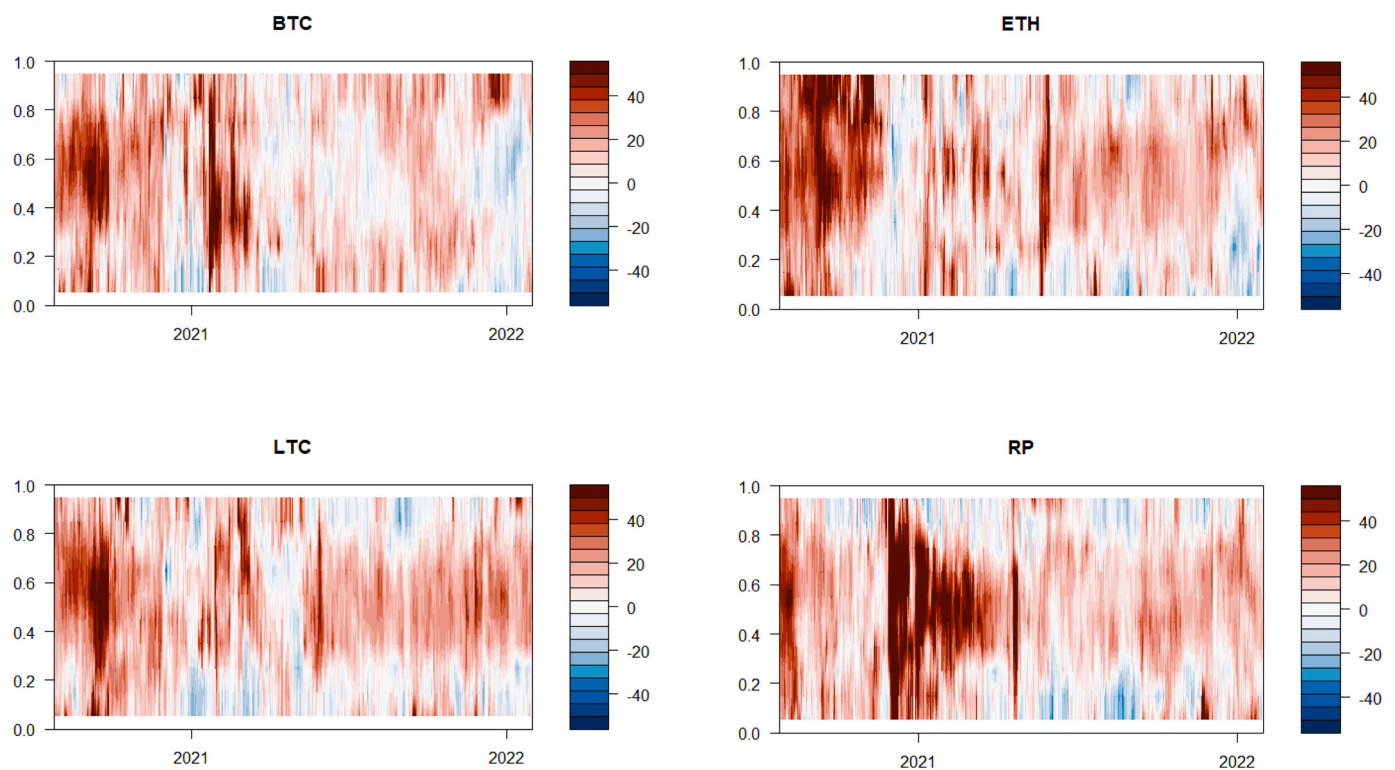
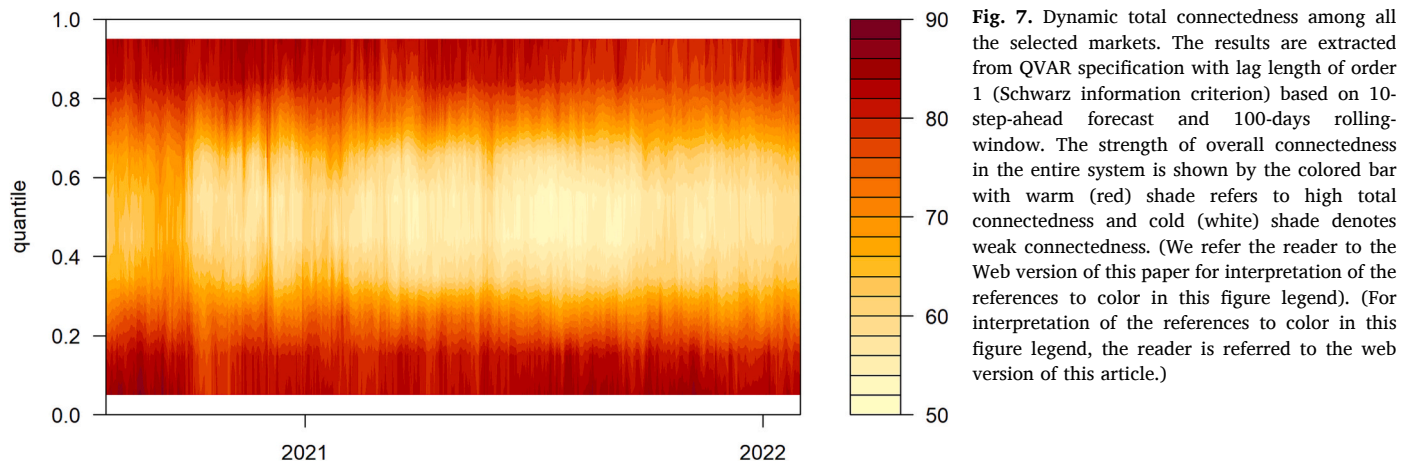
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Fig. 6. Network visualization of the net pairwise weighted average directional shock spillovers of the whole system including green bonds, cryptocurrencies, and COVID-19 indicators under bearish (a), normal (b), and bullish (c) markets. Notes: the edges indicate the direction of shock spillovers among markets and the size of each edge presents the magnitude of intensity for the net connectedness. The size and color of each node present the overall scale and strength of shock spillovers with blue (yellow) reflects net sender (taker) of risk spillover. (We refer the reader to the Web version of this paper for interpretation of the references to color in this figure legend.) (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We start by examining the static spillover transmission mechanism in green bond markets, cryptocurrencies, and uncertainty induced by the COVID-19 pandemic. This approach allows for the detection of the extent to which expectations in the markets change in reaction to events in other markets and how connectedness between different markets evolves. We analyzed the static spillover effects of cryptocurrencies and COVID-19 pandemic-related uncertainties on the green bonds market at bear (extreme lower quantile; $\tau = 0.05$, normal (middle quantile; $\tau = 0.50$) and bullish (extreme upper quantile; $\tau = 0.95$) market states. Tables 3–5 present the results respectively for $\tau = 0.05$, $\tau = 0.50$, and $\tau = 0.95$. Overall, the results showed that the static spillover effects at the extreme lower and extreme upper quantiles were stronger than those at the middle quantile. From the total directional spillover perspective, at bear and bullish market states, the static spillover effect from all indexes exceeded 81.41% for both green bonds and cryptocurrency systems, whereas the static spillovers from all indexes at the stable markets were <54.75% for the three green bond indexes and the four cryptocurrencies. Further, it is important to highlight that green bond indexes, as well as cryptocurrencies, were affected by the uncertainty related to the COVID-19 pandemic (PANIC, MEDIA_HYPE, FAKE_NEWS, SENTIMENT, INFODEMIC, and MEDIA_COVERAGE) to a large extent in the extreme lower and extreme upper market states. Furthermore, according to Tables 3–5, it appears that all the cryptocurrencies were mostly the highest net contributors to volatility shocks. Concerning green bonds, these assets were net contributors in most cases. These findings confirm Huynh et al.'s (2020) results showing that BTC and green bonds are shock senders. Similarly, Le et al.'s (2021) investigation of the spillover among Fintech, green bonds, and cryptocurrencies using daily data from November 2018 to June 2020 highlighted BTC as a net contributor to volatility shocks, whereas green bonds and green bond selections were net receivers.

The last rows of Tables 3–5 contain the net volatility spillover effects for each index, quantifying the input by each of them to the global volatility. The six indexes related to the COVID-19 pandemic had the highest spillover value, regardless of the market scenario. This implies that coronavirus pandemic uncertainty was the biggest contributor to the green bonds and cryptocurrencies markets. This outcome underlines the fact that the COVID-19 data reported amplifies financial volatility. Albulescu (2021) reports similar results as the official announcements regarding the COVID-19 new cases of infection and fatality ratio positively influence the financial markets' volatility in the U.S. Consistently, Onan, Salih, and Yasar (2014) reported that macroeconomic announcements affect the high-frequency behavior of the implied volatility of S&P 500 index options and VIX.

Regarding the connectedness between green bonds and cryptocurrencies, cryptocurrency markets statically produce volatility spillovers to green bonds under extreme negative market conditions (values between 6.63% and 7.67%) and extreme positive market conditions (values between 6.36% and 7.43%). Cryptocurrency markets transmitted 27.96% to the global MSCI green bond, 28.03% to the MSCI Euro green bond, and 27.78% to the S&P green bonds under the bullish market. This indicates that cryptocurrency markets highly affected green bond markets when the market was bullish. Similar behavior was also observed when the market was bearish. This may suggest that



economic actors, enclosing investors, and policymakers are sensitive to the nature of market states, whether bearish or bullish. By contrast, the net pairwise information connectedness presented in Fig. 6 shows that cryptocurrency markets' net transmitted shocks to all green bond markets in all market circumstances, with the dominance of BTC, particularly when the market is bearish. This finding may imply that the net influence of BTC on green bonds is larger than that of ETH, XRP, and LTC. Therefore, the dominance of the BTC market might be attributed to rising trends in BTC investments by investors and decision makers around the world. Overall, we presume that the four cryptocurrency markets under concern are highly integrated with green bonds in terms of the return transfer mechanism, particularly under negative market events. Investors and policymakers should be aware of the assessment of

the effect of cryptocurrency shock spillovers on green bonds during the COVID-19 health crisis, specifically when markets are bearish and/or bullish, and should flexibly formulate optimal crypto-green bond portfolios to make more benefits and avoid risks.

The static connectedness of volatility spillovers between markets is depicted in Figs. 3–5 in the heatmap visualization. The extent of the intensity of market pair volatility spillovers is shown by the colored bar. Darker-colored cells indicate high volatility connectedness, whereas lighter-colored cells indicate weak volatility spillover connectedness. The results showed that in bearish and bullish states, the volatility spillover connectedness pairwise was higher than in normal scenarios, as shown by several darker-colored cells. As shown in Fig. 3, media coverage presents strong volatility spillover transmission (14.17) with

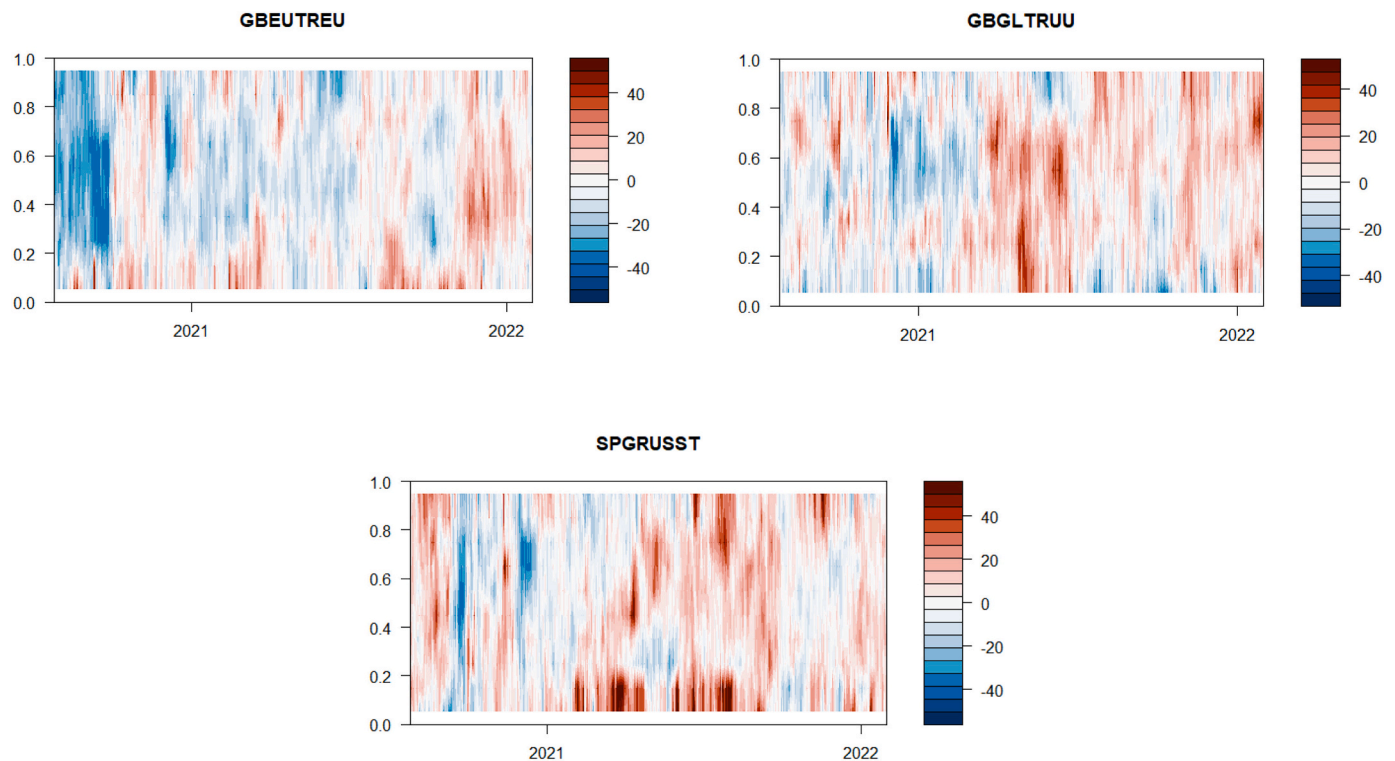


Fig. 9. Heatmap visualization of the net directional spillovers connectedness of green bond markets for quantile range [0.05, 0.95] and across time. Notes: see note in Fig. 8. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

green bonds (SPGRUSST). In addition, the ETH-GBGLTRUU pair showed a high volatility connectedness coefficient (13.44), which suggests that ETH and green bonds were highly connected under extreme market risk. Volatility spillover connectedness was weak under normal conditions (Fig. 4), as denoted by a brighter-colored heatmap matrix. This may demonstrate that COVID-19 uncertainty and cryptocurrencies had a weak effect on green bonds when the market was stable. Fig. 5 shows that the volatility spillover connectedness between market pairs was more intense, as indicated by numerous darker-colored cells in the heatmap.

The results of static volatility spillover connectedness displayed in Figs. 3–5 show that the volatility spillover effects of COVID-19 uncertainty and cryptocurrencies on green bonds were more intense under market pressure (bearish and bullish states). These results are consistent with those of Balçilar, Ozdemir, and Wohar (2020), Bouri, Lucey, Saeed, and Vo (2020), and Saeed, Bouri, and Alsulami (2021), who found that extreme shocks strongly affect spillovers between markets more than in stable conditions.

4.2. Network of shock spillovers and transfer paths

Herein, we visualize a network of net pairwise directional spillover connectedness among green bonds, cryptocurrencies, and COVID-19 uncertainties at extreme lower and extreme upper quantiles, as well as the median quantile of the joint distribution. However, our aim is to show whether a variable in the whole system is a net sender or a net taker of shock spillovers.

The results are portrayed in the network diagrams in Fig. 6 (a, b, c). Each network shows the net directional shock spillovers of each market in the entire system. As shown in Fig. 6a, the MSCI Euro green bond market acted as the leading net taker of shocks in the system, followed by the S&P green bond and MSCI global green bond. The strongest shock spillover effect was exerted by fake news and BTC. This result reveals that the fake news of COVID-19 and BTC highly affected green bond markets under extreme business market downwards. Similarly, media

coverage seemed to be the third net sender of shock spillovers to green bond markets in the entire system. Fake news appeared to be the leading net sender of shock spillovers to all other markets, followed by BTC.

Under the bullish market (Fig. 6c), all cryptocurrencies acted as net senders of shock spillovers to all other markets, with ETH being the dominant net sender of risk. Compared to the bearish market, the bullish market showed that green bonds (GBEUTREU and SPGRUSST) acted as net takers of shock spillovers from others. Further, in bullish circumstances, green bonds (GBGLTRUU) appeared as net senders of shock spillovers. Thus, the MSCI global green bond market switched from a net shock spillover taker in the bearish market to a net sender of shocks in the bullish market. This may be due to the switching of its net shock spillover amounts from negative to positive.

Under the normal market (Fig. 6b), the network graph shows very thin edges, indicating weak net connectedness between green bonds, cryptocurrencies, and COVID-19-related news in the entire system. The exception was registered between cryptocurrency pairs, as well as between PANIC-INFODEMIC and MEDIA_COVERAGE-MEDIA_HYPE pairs. Furthermore, LTC and ETH acted as the greatest net senders of shock spillovers to other markets.

To summarize, the net pairwise directional spillover diagrams displayed in Fig. 6 show a complex pattern of net connectedness between markets in bearish and bullish circumstances, in comparison to normal conditions. These results are in line with those found by Bouri, Saeed, Vo, and Roubaud (2021), Lin and Su (2021), Khalfaoui et al. (2022), and Elsayed et al. (2022). Further, the evidence of weak net pairwise directional connectedness between green bonds and cryptocurrencies at stable events suggests a potential diversification advantage based on the green bond–cryptocurrency pairwise.

4.3. Sensitivity to quantile analysis of shock spillovers

4.3.1. Dynamic overall connectedness

After analyzing the static connectedness patterns among the variables, in this section, we focus on the dynamic overall and net

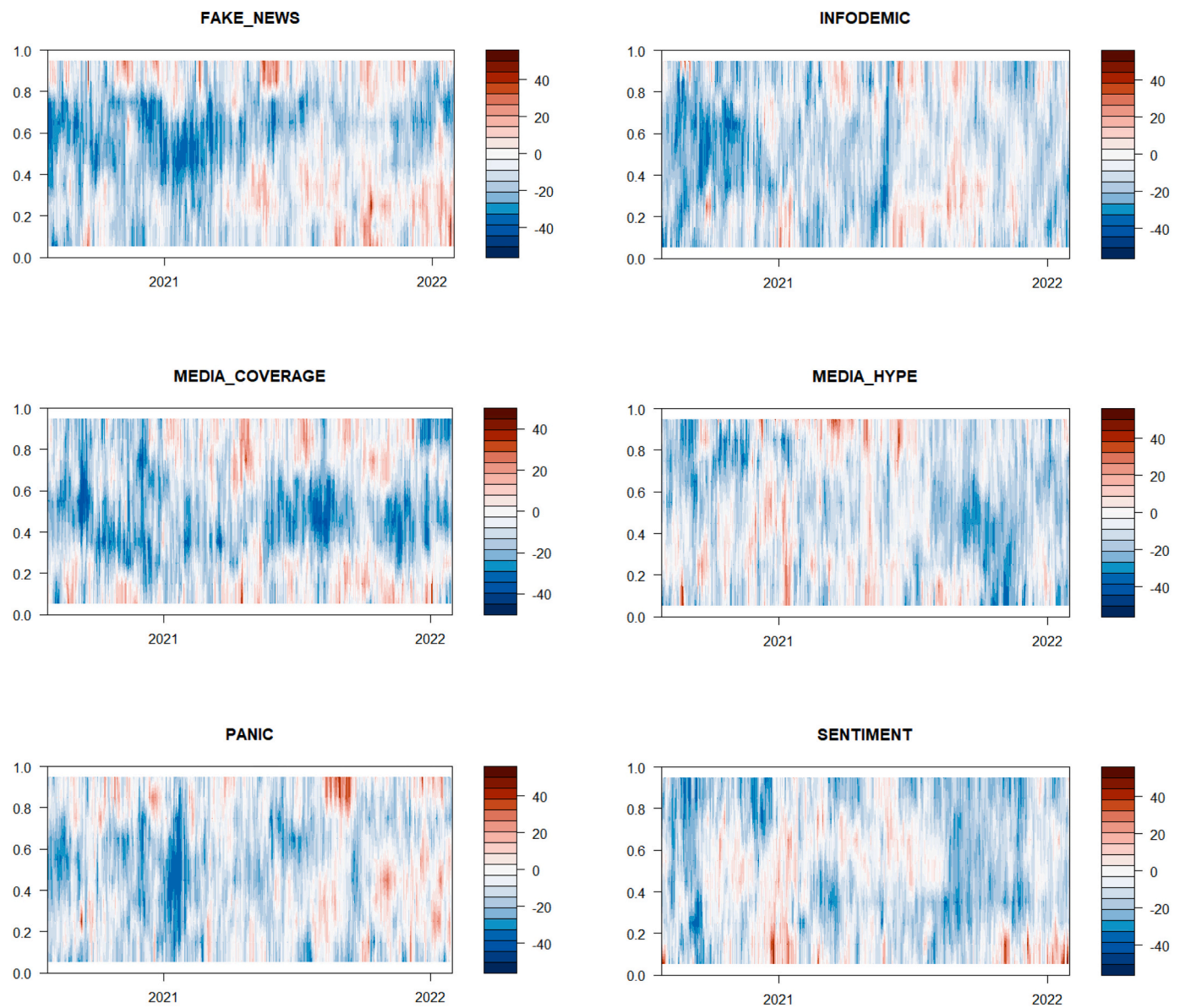


Fig. 10. Heatmap visualization of the net directional spillovers connectedness of COVID-19 uncertainties for quantile range $[0.05, 0.95]$ and across time. Notes: see note in Fig. 8.

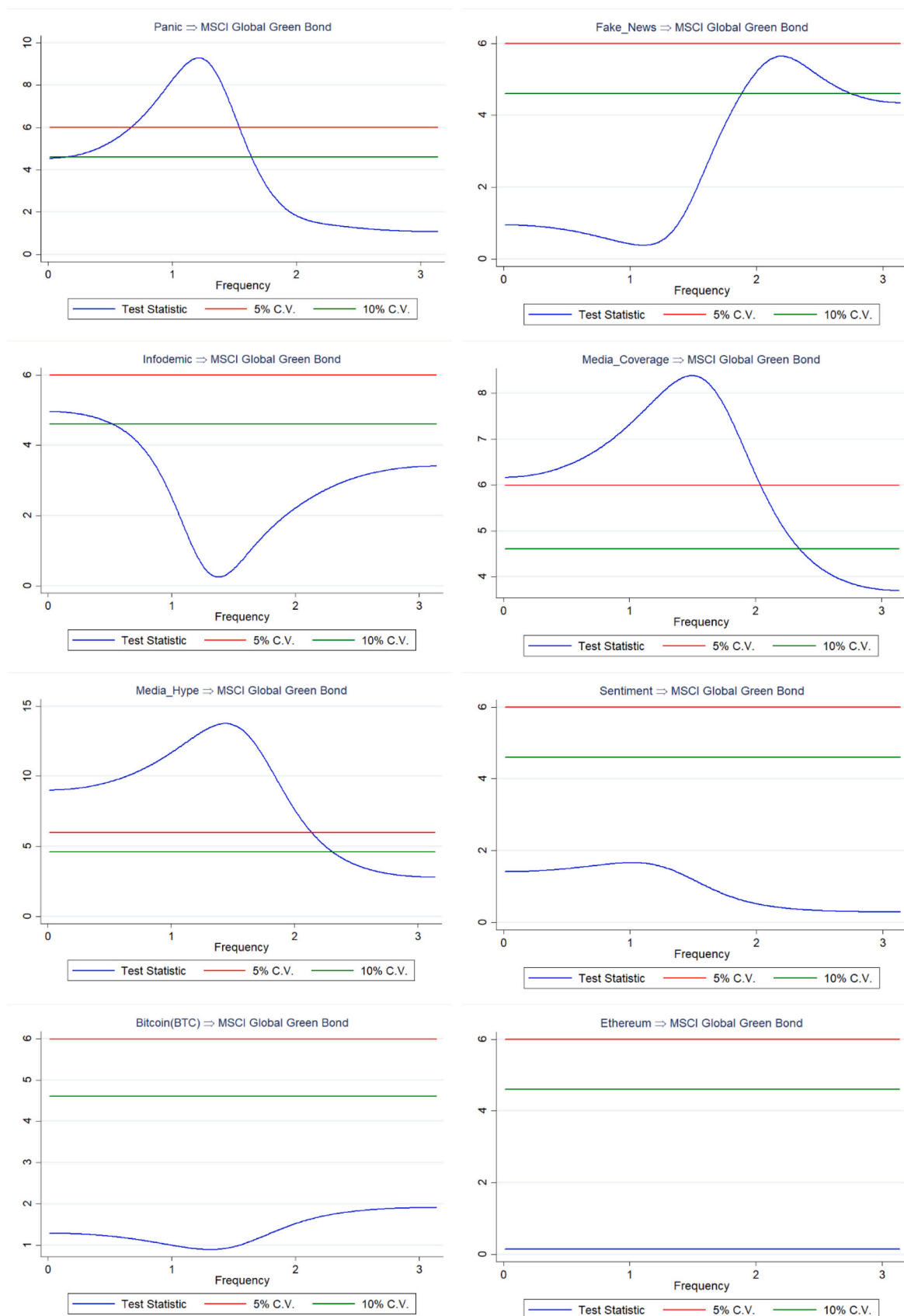


Fig. 11. Breitung-Candelon spectral Granger causality test: causality from COVID-19 uncertainty and cryptocurrencies to MSCI global green bond. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

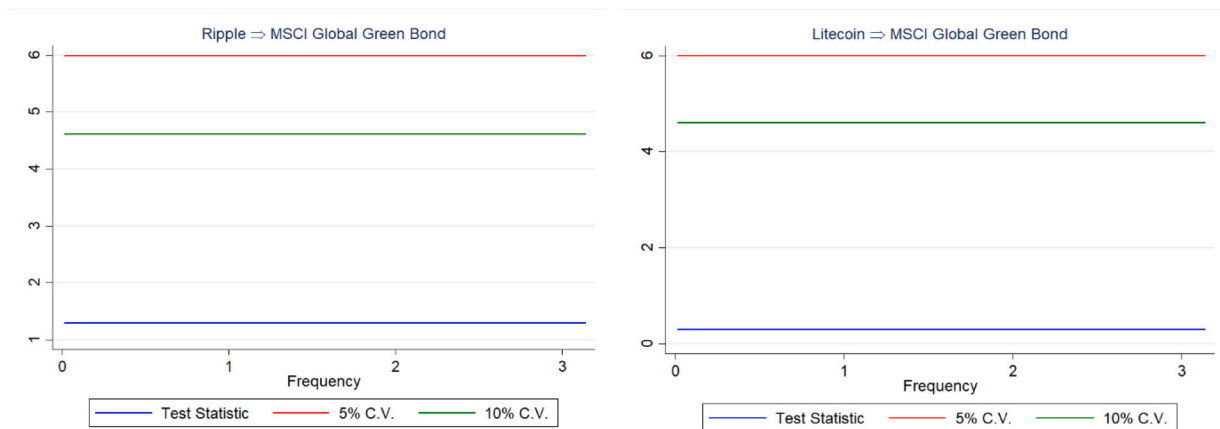


Fig. 11. (continued).

connectedness in the market system. Fig. 7 graphs the dynamic overall connectedness between green bonds, cryptocurrencies, and COVID-19-related news at quantile range $[0.05, 0.95]$ and during the entire period under concern. As we show in Fig. 7, the dynamic overall connectedness was very large at quantile intervals $[0.05, 0.3]$ and $[0.7, 0.95]$. From the heat map, it is evident that the dynamic overall connectedness was symmetric. We also observed that in 2020 and at the beginning of 2021, the dynamic overall connectedness was very large at all market circumstances, that is, for all quantile $\tau \in [0.05, 0.95]$ as given by the huge warmer shade. This phenomenon may be due to the first and second COVID-19 waves, which severely affected the dynamic changes in green bonds and cryptocurrencies. Furthermore, it is clearly noticeable from the heatmap (Fig. 7) that once COVID-19 vaccines were discovered, the overall connectedness became very weak at the quantile range $[0.3, 0.7]$, suggesting a very low interdependency between markets. In fact, the effects of COVID-19 uncertainties were very weak under stable market events.

4.3.2. Net total connectedness

To better understand the dynamic net spillover connectedness of each market, we visualize the net connectedness over a broad spectrum of quantiles for the joint distribution spanning from $\tau = 0.05$ to $\tau = 0.95$ with 1% step. The results are charted in heatmap matrices (Figs. 8–10). A net sender of a shock spillover market is reflected by warmer shades in the heatmap, while a net shock spillover taker is designed by a colder color. In other words, a net information spillover sender to others is shown by red-colored isles, whereas a net information spillover taker from others is presented by blue shades.

As shown in Fig. 8, the warmer shades are more pronounced in the heatmaps, particularly at the beginning of the sample study, indicating that cryptocurrencies are net information spillovers sender to green bond markets. The results revealed that volatility changes in cryptocurrencies affected the future volatility of green bonds under all market scenarios and periodicities. At the beginning of 2021, Ripple cryptocurrency appeared as the largest net information spillover sender to green bond markets in the system. Additionally, as shown in Fig. 9, the MSCI Euro green bond acted as the greatest net shock taker from the others, as shown by many blue isles in the heat map. Interestingly, the Bloomberg MSCI Euro green bond was a net taker of information spillovers during 2020 over all quantile ranges. This result is not surprising,

as it coincides with the COVID-19 outbreak, and the pandemic hit hard on economies of the world. Nevertheless, COVID-19 uncertainties played a significant role in the net behavior of green bond markets. Furthermore, we found that green bonds appeared to assume both roles across quantiles and over time periods. More importantly, the three green bonds used in the study shifted to weak net information spillovers sender to others during 2022. A plausible explanation for such a transfer mechanism in 2022 is that COVID-19 vaccination may have significantly and positively affected green bond volatility.

The heatmaps presented in Fig. 10 display the net information spillover connectedness of COVID-19 uncertainty variables. The net information spillover transmission pattern among the six uncertainties was time-varying and quantile-dependent. Therefore, the net shock spillover connectedness of the COVID-19 uncertainties was more complex, and each COVID-19 uncertainty played both roles in the system. The net information spillover connectedness results corroborate those discussed in the network connectedness analysis presented in Section 4.2.

5. Frequency domain granger causality analysis

In this section, we use the spectral Granger causality test following Breitung and Candelon (2006). For more details about the method, we refer the reader to Breitung and Candelon (2006). This causality tool allows us to examine causality tests in the sense of Granger under the frequency domain. We can also investigate the nonlinear causal link between variables at all business cycles, including short-term (high frequency) and long-term (low frequency) horizons. The results of frequency Granger causality running from cryptocurrencies and COVID-19 uncertainties to green bond markets are presented in Figs. 11–13. The results were obtained from frequency (ω) range $(0, \pi)$. Table 6 presents the selected optimal lags for the different VAR models based on the Akaike information criterion (AIC) and the Schwarz Bayesian information criterion (BIC).

As shown in Fig. 11, the majority of COVID-19 uncertainties Granger caused MSCI global green bonds, except that the sentiment index did not cause this green market. At the short-term horizon, panic, infodemic, media coverage, and media hype Granger caused MSCI global green bonds, suggesting that the prediction of global green bond volatility is highly influenced by future pandemic uncertainties. By contrast, the

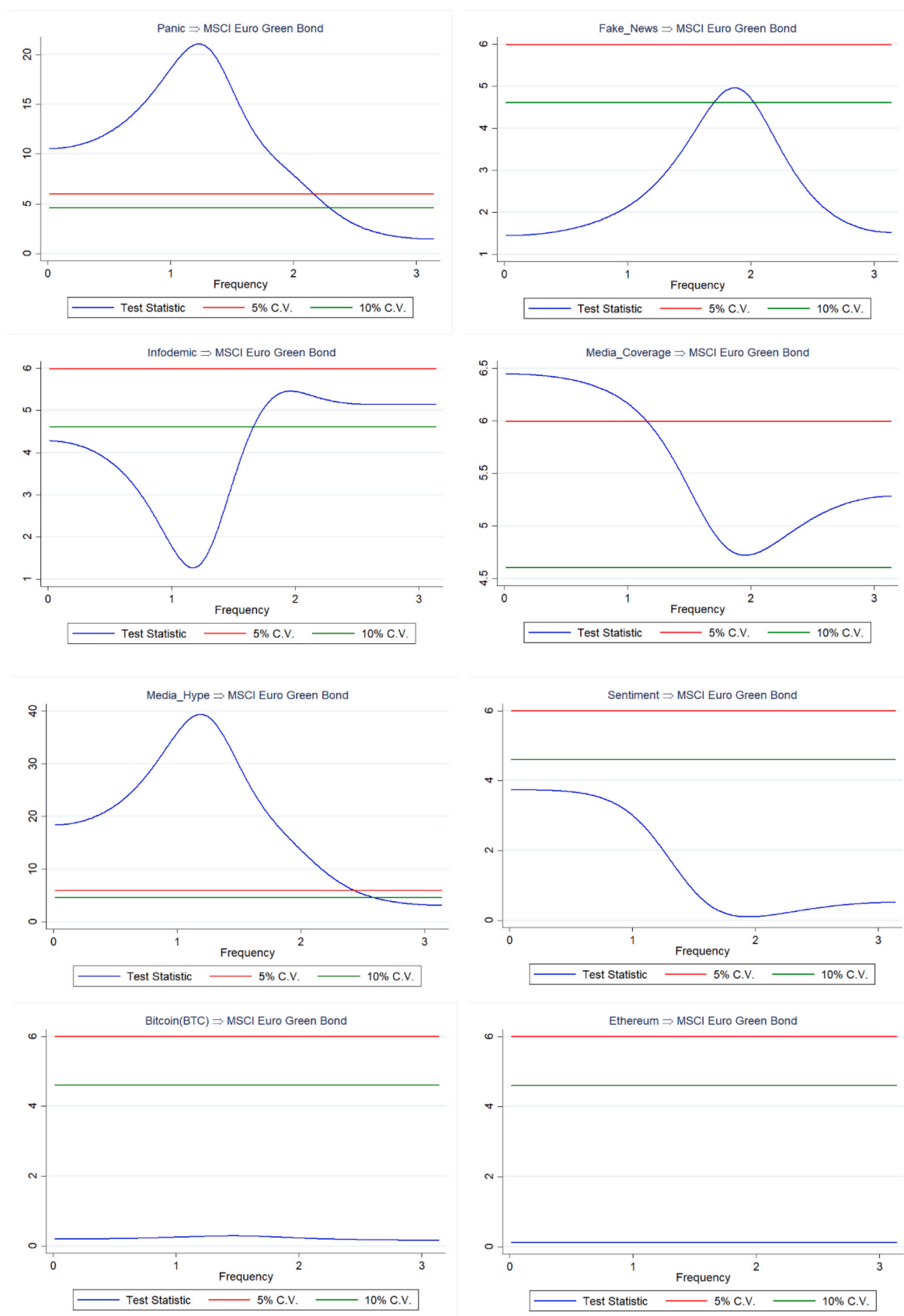


Fig. 12. Breitung-Candelon spectral Granger causality test: causality from COVID-19 uncertainty and cryptocurrencies to MSCI Euro green bond. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

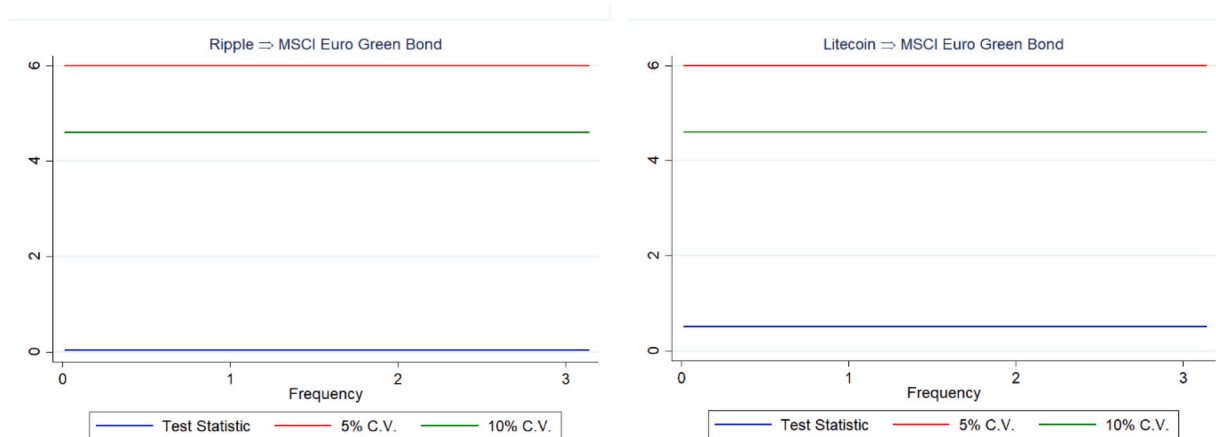


Fig. 12. (continued).

results show no Granger causality running from cryptocurrencies to MSCI global green bonds.

We further carried out two exercises. Exercise 1 tested the spectral Granger causality for the effects running from the COVID-19 pandemic and cryptocurrencies to MSCI Euro green bond volatility (Fig. 12). Referring to Fig. 12, we documented causal flow running from panic, media coverage, and media hype to MSCI Euro green bond at short- and medium-term business cycles, whereas infodemic Granger caused Euro green bond at the long-term investment business cycle (at a 10% significance level). Furthermore, there was no significant causal association between sentiment and the MSCI Euro green bond.

Exercise 2 provides a causal effect according to the S&P green bond case. The results are displayed in Fig. 13. We obtained strong evidence that media hype Granger caused S&P green bonds at all frequencies ($\omega \in [0, \pi]$). Further, information and media coverage caused S&P green bonds to fall under the short-term business cycle. For the frequency range $\omega \in [1.2, 1.4]$, we find (at 5% significance level) an inverted U-shape causal effect running from the panic index to the S&P green bond market. We found no causal connection between cryptocurrencies and the S&P green bond market. Overall, the frequency domain Granger causality exercise highlights a more pronounced causal effect running from panic and stress motivated by the COVID-19 pandemic to the three green bond markets used in the short-term business cycle.

6. Conclusion and implications

The current pandemic crisis has gradually morphed into a record downturn in financial markets. Such circumstances have forced investors to look for alternative strategies for portfolio investment. Unarguably, the major economies of the world are adopting stimulus packages to bring resilience to the economy. Simultaneously, the countries are devising strategies that are augmenting climate welfare. Against this backdrop, the exploration of the properties of major green bonds as crucial instruments of alternative financial investments has been a topic of discussion in the literature. The current study adds to the deliberations in the empirical literature by investigating the role of stress and panic owing to COVID-19 in the green bonds market and a major emerging market—the cryptocurrency market. Such an analysis

provides essential insights that may enable financial investors to identify alternative avenues for investment during turbulent situations. To this end, we applied six uncertainty indicators to the COVID-19 pandemic, alongside three major green bond indices and four important cryptocurrency indices. The major pandemic-related indices included are the Coronavirus Panic Index, Coronavirus Media Hype Index, Coronavirus Fake News Index, Global Sentiment Index, Coronavirus Infodemic Index, and Coronavirus Media Coverage Index. The major green bond markets chosen are Bloomberg MSCI Global Green Bond Index, Bloomberg MSCI Euro Green Bond Index, and S&P Green bond U.S. Dollar Select Index. The cryptocurrency markets are in four categories: BTC, ETH, RP, and LTC. The period of observation was from January 1, 2020 to January 31, 2022.

To add novel insights to the empirical analysis, we adopted the asymmetric framework of analysis and provided rich evidence concerning the correlation between markets under differing conditions: bearish, bullish, and normal. This study utilized the DY method by Diebold and Yilmaz (2012, 2014) and the quantile regression technique postulated by Ando et al. (2022) to investigate time-varying spillover connectedness across markets and to measure the direction of the net transmission effect under varying market conditions.

The results of the net pairwise directional spillover between the markets display a complex pattern of interrelationships, particularly during extreme market situations. Furthermore, the empirical outcome of weak net pairwise directional connectedness between green bonds and cryptocurrency during normal times reports information on pairwise diversification benefits across these two markets. Based on the dynamic net spillover analysis across the quantile in the joint distribution, we found that cryptocurrency markets were the net volatility senders to green bond markets. Unarguably, the analysis demonstrated that the COVID-19 uncertainty indices have complex interconnectedness with green bond markets and cryptocurrency markets. For example, the fake news index of COVID-19 largely affected green bonds during business downswings and upswings. There was a significant shock spillover from the media coverage index related to the pandemic to the green bond market.

The findings of this study have several implications. The outcomes of this research offer fresh insights into portfolio diversification for market

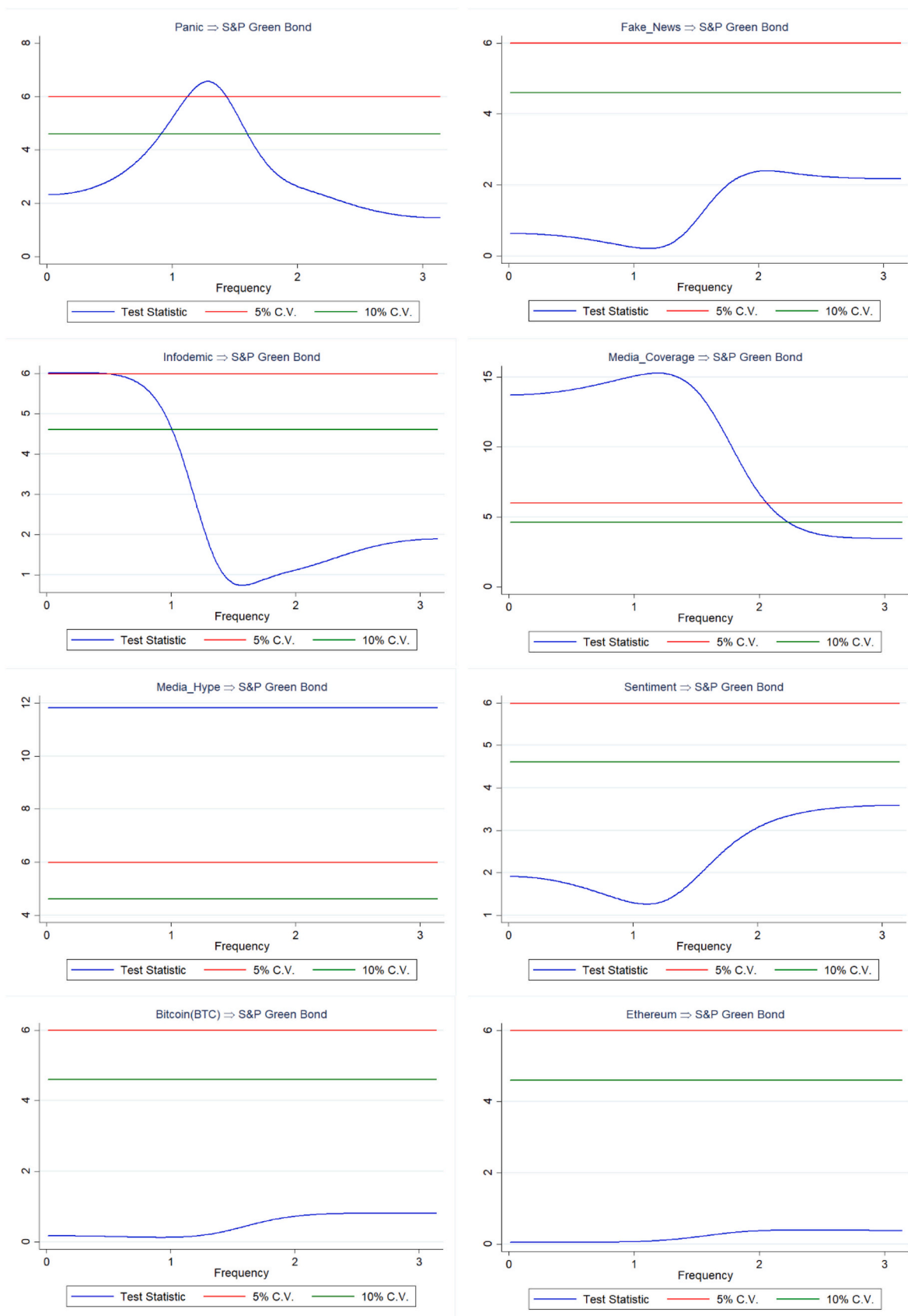


Fig. 13. Breitung-Candelon spectral Granger causality test: causality from COVID-19 uncertainty and cryptocurrencies to S&P green bond. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

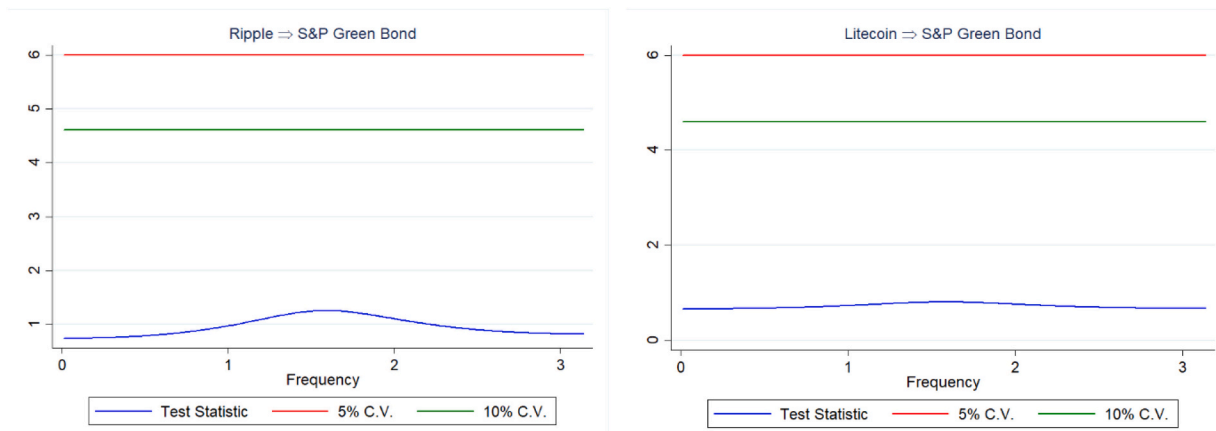


Fig. 13. (continued).

Table 6

Optimal lag-order selection for VAR models according to information criterion AIC and BIC.

	AIC	BIC
MSCI Euro green bond		
GBEUTREU – BTC	1	1
GBEUTREU – ETH	2	1
GBEUTREU – RP	2	1
GBEUTREU – LTC	2	1
GBEUTREU – PANIC	4	4
GBEUTREU – MEDIA_HYPE	4	2
GBEUTREU – FAKE_NEWS	4	3
GBEUTREU – SENTIMENT	1	1
GBEUTREU – INFODEMIC	4	4
GBEUTREU – MEDIA_COVERAGE	3	1
MSCI global green bond		
GBGLTRUU – BTC	1	1
GBGLTRUU – ETH	2	1
GBGLTRUU – RP	2	1
GBGLTRUU – LTC	2	1
GBGLTRUU – PANIC	4	4
GBGLTRUU – MEDIA_HYPE	3	2
GBGLTRUU – FAKE_NEWS	4	4
GBGLTRUU – SENTIMENT	1	1
GBGLTRUU – INFODEMIC	4	4
GBGLTRUU – MEDIA_COVERAGE	3	1
S&P green bond		
SPGRUSST – BTC	2	1
SPGRUSST – ETH	2	1
SPGRUSST – RP	2	1
SPGRUSST – LTC	2	1
SPGRUSST – PANIC	4	4
SPGRUSST – MEDIA_HYPE	4	2
SPGRUSST – FAKE_NEWS	4	4
SPGRUSST – SENTIMENT	1	1
SPGRUSST – INFODEMIC	4	4
GBEUTREU – MEDIA_COVERAGE	4	1

investors. The findings enable policy planners to draw strategies on sustainable development concerns and the future of green bond markets. From the perspective of investors, our study calls for diversification of investments. Empirical results on the dynamic connectedness between green bonds and cryptocurrency markets provide new insights for investors who want to decarbonize their portfolios by investing in green assets to diversify their portfolios. Thus, it appears that investors should

combine green bonds in their portfolios to obtain incremental diversification benefits. Further, the study suggests that, based on the dynamism of the green bond markets, policy planners could utilize this market for attaining the twin objective of sustainable development and bringing resilience to the economy after the pandemic. Strategic investments in the green energy sector will enable major governments to reboot the economy and attain climate welfare-enhancing targets alongside the sustainable development goal. To this end, policy planners are advised to explore strategies for attaining the United Nations Sustainable Development Goal 13 on climate action and Goal 17 for developing cooperation and partnerships to achieve environmental sustainability. Uplifting investment policies on climate welfare may enhance green bond markets. Such strategies are expected to make green bonds more robust to conditions of uncertainty. We advise that governments in different countries should be in active partnerships to promote the efficacy of the green bond market.

For future directions in research, we advocate that further studies be explored to scrutinize the implications of varying measures of uncertainty emanating from health risks, such as those from political instability, climate risks, and macroeconomic uncertainty, among others. These characteristic features progressively impact investors' decisions on portfolio diversification in the context of green bonds. Additionally, future research may contribute to the extant deliberations by inspecting the impact of climate policy variables, such as climate tax and public support programs on green technology, and how they may drive green bond markets. Regarding the methodology of estimation, further research may consider testing portfolio performance using other novel estimation techniques, such as minimum correlation portfolio and minimum connectedness portfolio (Tiwari et al., 2022), conducting analysis based on copula method (Mzoughi et al., 2022), and constructing time-varying parameter vector autoregression models (Chai, Chu, Zhang, Li, & Abedin, 2022).

CRediT authorship contribution statement

Rabeh Khalfaoui: Conceptualization, Software, Methodology, Formal analysis, Visualization, Data curation, Validation, Writing – original draft, Writing – review & editing. **Salma Mefteh-Wali:** Conceptualization, Formal analysis, Writing – review & editing, Data curation, Methodology. **Buhari Dogan:** Conceptualization, Formal analysis, Writing – review & editing, Methodology. **Sudeshna Ghosh:** Conceptualization, Methodology, Formal analysis, Writing – review & editing.

Appendix A. Appendix

Table A1

Summary of studies in the recent literature on green bonds and other financial markets.

Authors	Period	Main Variables	Methodology	Major Findings
Mzoughi et al. (2022)	July 2014 to September 2020.	Green bonds, energy commodity markets.	Copula's methods.	Green bonds) are significantly impacted by considerable price spillovers from energy commodity market during periods of market turbulence.
Elsayed et al. (2022)	September 2014 to June 2020.	Green bonds, treasury, corporate bond, stock, and clean energy markets.	Wavelet Analysis and Ensemble Empirical Mode Decomposition methods.	The outcomes on dynamic connectedness demonstrate interconnectedness amid green bonds and financial markets. Further, it is volatile over time.
Tiwari et al. (2022)	January, 2015 to September 2020	Green bonds.	Time-varying parameter vector autoregression model.	The results demonstrate the hedging effectiveness property even during the pandemic.
Khalfaoui et al. (2022)	July 2014 to June 2021.	Green bonds, bitcoins and US stock market.	Quantile vector autoregressive connectedness method.	Bitcoin were found to be net recipients of shock spillovers, while most green bonds were net contributors.
Abakah, Tiwari, Sharma, and Mwamtambulo (2022)	4, January 2015 to 22, September 2020.	Different green bond markets.	Time-varying parameter vector autoregression model.	Green bonds major recipients of shocks. The same pattern exists during the period of the COVID-19 pandemic.
Chai et al. (2022)	01, July 2011 to 09, July 2021	Green bonds, stock prices, clean energy stocks.	Time-varying parameter vector autoregression model.	The results of impulse responses at different time horizons show that green bonds cause a short-term increase in clean energy stocks, and it creates an increasingly positive impact specifically during the COVID-19 outbreak
Pham and Huynh (2020)	October 2014 to February 2021.	Green bonds, energy markets and stock markets.	Cross-quantilogram method.	The empirical results demonstrate that the spillover between asset classes and green bonds differ extensively between the quantiles. The results further demonstrate the variation in hedging benefits of green bonds particularly during extreme market conditions.
Naeem and Karim (2021)	May 2013 to July 2021.	Green bonds and bitcoins.	Time varying optimal copula method.	The hedging effectiveness of green bonds for bitcoin is demonstrated.
Le et al. (2021)	November 2018 to June 2020.	Fintech, gold, oil green bonds and cryptocurrencies.	Diebold & Yilmaz, (2012) and (Barunik et al., (2017) to estimate volatility connectedness.	Bitcoins are net contributors to shocks. The traditional assets for example gold and oil, and the modern assets, green bonds, are an example of good hedgers.
Piñeiro-Chousa, López-Cabarcos, Caby, and Šević (2021)	January 2018 to November 2018	4 major green bond markets.	GMM estimation methods.	The crucial influence of social networks is found to impact the green bonds.
Reboredo and Ugolini (2020)	October 2014 to December 2018.	Green bonds, stocks and energy commodities.	Multi-vector autoregressive model.	The green bond market has a strong association with currency and fixed-income markets. Green bonds demonstrate a weak linkage effect with energy markets.
Nguyen et al. (2021)	2008 to 2019.	Green bonds, stocks, commodities and clean energy.	Rolling window wavelet method.	Strong co-movements across the markets.
Huynh et al. (2020)	2017 to 2020	Green bonds, gold markets, artificial intelligence stocks, bitcoins.	Generalized Forecast Error Variance. Decomposition and Copulas.	The tail dependence structure across markets predicts high losses during turbulent market periods. Bitcoins and gold demonstrate high-hedging properties.

References

- Abakah, E. J. A., Tiwari, A. K., Sharma, A., & Mwamtambulo, D. J. (2022). Extreme connectedness between green bonds, government bonds, corporate bonds and other asset classes: Insights for portfolio investors. *Journal of Risk and Financial Management*, 15, 477. <https://doi.org/10.3390/jrfm15100477>
- Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID-19 crisis. *Finance Research Letters*, 38, Article 101604. <https://doi.org/10.1016/j.frl.2020.101604>
- Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, 38, Article 101699. <https://doi.org/10.1016/j.frl.2020.101699>
- Ando, T., Greenwood-Nimmo, M., & Shin, Y. (2022). Quantile connectedness: Modeling tail behavior in the topology of financial networks. *Management Science*, 0(0). <https://doi.org/10.1287/MNSC.2021.3984>
- Arif, M., Naeem, M. A., Farid, S., Nepal, R., & Jamasb, T. (2021). Diversifier or more? Hedge and safe haven properties of green bonds during COVID-19. URL: <https://doi.org/10.2139/ssrn.3782126>.
- Atri, H., Kouki, S., & imen Gallali, M. (2021). The impact of COVID-19 news, panic and media coverage on the oil and gold prices: An ARDL approach. *Resources Policy*, 72, Article 102061.
- Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2021). Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. *Finance Research Letters*, 38, Article 101701.
- Balcilar, M., Ozdemir, Z. A., Ozdemir, H., & Wohar, M. E. (2020). *Transmission of US and EU economic policy uncertainty shock to Asian economies in bad and good times*. Available at SSRN 3602333.
- Bariviera, A. F., & Merediz-Solà, I. (2021). Where do we stand in cryptocurrencies economic research? A survey based on hybrid analysis. *Journal of Economic Surveys*, 35(2), 377–407. <https://doi.org/10.1111/joes.12412>
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217–229. <https://doi.org/10.1111/J.1540-6288.2010.00244.X>
- Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23, 87–95. <https://doi.org/10.1016/j.frl.2017.02.009>
- Bouri, E., Lucey, B., Saeed, T., & Vo, X. V. (2020). Extreme spillovers across Asian-Pacific currencies: A quantile-based analysis. *International Review of Financial Analysis*, 72, Article 101605.
- Bouri, E., Saeed, T., Vo, X. V., & Roubaud, D. (2021). Quantile connectedness in the cryptocurrency market. *Journal of International Financial Markets Institutions and Money*, 71, Article 101302. <https://doi.org/10.1016/j.intfin.2021.101302>
- Bouteska, A., Mefteh-Wali, S., & Dang, T. (2022). Predictive power of investor sentiment for Bitcoin returns: Evidence from COVID-19 pandemic. *Technological Forecasting and Social Change*, 184, 121999.
- Breitung, J., & Candelon, B. (2006). Testing for short-and long-run causality: A frequency-domain approach. *Journal of Econometrics*, 132(2), 363–378.
- Broadstock, D. C., & Cheng, L. T. (2019). Time-varying relation between black and green bond price benchmarks: Macroeconomic determinants for the first decade. *Finance Research Letters*, 29, 17–22. <https://doi.org/10.1016/j.frl.2019.02.006>

- Cepni, O., Demirer, R., & Rognone, L. (2022). Hedging climate risks with green assets. *Economics Letters*, 110312. <https://doi.org/10.1016/j.econlet.2022.110312>
- Cepoi, C.-O. (2020). Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. *Finance Research Letters*, 36, Article 101658.
- Chai, S., Chu, W., Zhang, Z., Li, Z., & Abedin, M. Z. (2022). Dynamic nonlinear connectedness between the green bonds, clean energy, and stock price: The impact of the COVID-19 pandemic. *Annals of Operations Research*, 1-28. <https://doi.org/10.1007/s10479-021-04452-y>
- Conlon, T., Corbet, S., & McGee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Research in International Business and Finance*, 54, Article 101248. <https://doi.org/10.1016/j.ribaf.2020.101248>
- Corbet, S., Larkin, C., Lucey, B., & Yarovaya, L. (2020). KODAKCoin: A blockchain revolution or exploiting a potential cryptocurrency bubble? *Applied Economics Letters*, 27(7), 518–524. <https://doi.org/10.1080/13504851.2019.1637512>
- Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182–199. <https://doi.org/10.1016/j.irfa.2018.09.003>
- Dang, T. L., Dang, M., Hoang, L., Nguyen, L., & Phan, H. L. (2020). Media coverage and stock price synchronicity. *International Review of Financial Analysis*, 67, Article 101430.
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66. <https://doi.org/10.1016/j.ijforecast.2011.02.006>
- Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134.
- Dwyer, G. P. (2015). The economics of bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17, 81–91. <https://doi.org/10.1016/j.jfs.2014.11.006>
- Elsayed, A. H., Naifar, N., Nasreen, S., & Tiwari, A. K. (2022). Dependence structure and dynamic connectedness between green bonds and financial markets: Fresh insights from time-frequency analysis before and during COVID-19 pandemic. *Energy Economics*, 105842. <https://doi.org/10.1016/j.eneco.2022.105842>
- Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499–516.
- Giudici, P., & Polinesi, G. (2021). Crypto price discovery through correlation networks. *Annals of Operations Research*, 299(1), 443–457. <https://doi.org/10.1007/s10479-019-03282-3>
- Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, 63, 431–437. <https://doi.org/10.1016/j.irfa.2018.03.004>
- Guo, D., & Zhou, P. (2021). Green bonds as hedging assets before and after COVID: A comparative study between the US and China. *Energy Economics*, 104, Article 105696. <https://doi.org/10.1016/j.eneco.2021.105696>
- Han, Y., & Li, J. (2022). Should investors include green bonds in their portfolios? Evidence for the USA and Europe. *International Review of Financial Analysis*, 80, Article 101998. <https://doi.org/10.1016/j.irfa.2021.101998>
- Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, 27, Article 100343.
- Huynh, T. L. D., Hille, E., & Nasir, M. A. (2020). Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies. *Technological Forecasting and Social Change*, 159, Article 120188. <https://doi.org/10.1016/j.techfore.2020.120188>
- Kamal, J. B., & Hassan, M. K. (2022). Asymmetric connectedness between cryptocurrency environment attention index and green assets. *The Journal of Economic Asymmetries*, 25, Article e00240. <https://doi.org/10.1016/j.jeca.2022.e00240>
- Khalfaoui, R., Jabeur, S. B., & Dogan, B. (2022). The spillover effects and connectedness among green commodities, bitcoins, and US stock markets: Evidence from the quantile VAR network. *Journal of Environmental Management*, 306, Article 114493. <https://doi.org/10.1016/j.jenvman.2022.114493>
- Klibanoff, P., Lamont, O., & Wizman, T. A. (1998). Investor reaction to salient news in closed-end country funds. *The Journal of Finance*, 53(2), 673–699.
- Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1), 119–147. [https://doi.org/10.1016/0304-4076\(95\)01753-4](https://doi.org/10.1016/0304-4076(95)01753-4)
- Kuang, W. (2021). Are clean energy assets a safe haven for international equity markets? *Journal of Cleaner Production*, 302, Article 127006. <https://doi.org/10.1016/j.jclepro.2021.127006>
- Le, T. L., Abakah, E. J. A., & Tiwari, A. K. (2021). Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change*, 162, Article 120382. <https://doi.org/10.1016/j.techfore.2020.120382>
- Liang, Q., Sun, W., Li, W., & Yu, F. (2021). Media effects matter: Macroeconomic announcements in the gold futures market. *Economic Modelling*, 96, 1–12.
- Lin, B., & Su, T. (2021). Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities? *Research in International Business and Finance*, 56, Article 101360.
- Liu, T., & Gong, X. (2020). Analyzing time-varying volatility spillovers between the crude oil markets using a new method. *Energy Economics*, 87, Article 104711.
- Mzoughi, H., Urom, C., & Guesmi, K. (2022). Downside and upside risk spillovers between green finance and energy markets. *Finance Research Letters*, 102612. <https://doi.org/10.1016/j.frl.2021.102612>
- Naeem, M. A., Farid, S., Ferrer, R., & Shahzad, S. J. H. (2021). Comparative efficiency of green and conventional bonds pre-and during COVID-19: An asymmetric multifractal detrended fluctuation analysis. *Energy Policy*, 153, Article 112285. <https://doi.org/10.1016/j.enpol.2021.112285>
- Naeem, M. A., & Karim, S. (2021). Tail dependence between bitcoin and green financial assets. *Economics Letters*, 208, Article 110068. <https://doi.org/10.1016/j.econlet.2021.110068>
- Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O., & Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters*, 40, Article 101739. <https://doi.org/10.1016/j.frl.2020.101739>
- Onan, M., Salih, A., & Yasar, B. (2014). Impact of macroeconomic announcements on implied volatility slope of SPX options and VIX. *Finance Research Letters*, 11(4), 454–462. <https://doi.org/10.1016/j.frl.2014.07.006>
- Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17–29. [https://doi.org/10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0)
- Pham, L., & Huynh, T. L. D. (2020). How does investor attention influence the green bond market? *Finance Research Letters*, 35, Article 101533. <https://doi.org/10.1016/j.frl.2020.101533>
- Pham, L., Huynh, T. L. D., & Hanif, W. (2021). *Cryptocurrency, green and fossil fuel investments*. URL: <https://doi.org/10.2139/ssrn.3925844>.
- Pineiro-Chousa, J., López-Cabarcos, M. Á., Caby, J., & Šević, A. (2021). The influence of investor sentiment on the green bond market. *Technological Forecasting and Social Change*, 162, Article 120351. <https://doi.org/10.1016/j.techfore.2020.120351>
- Reboredo, J. C., & Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling*, 88, 25–38. <https://doi.org/10.1016/j.econmod.2019.09.004>
- Saeed, T., Bourli, E., & Alsulami, H. (2021). Extreme return connectedness and its determinants between clean/green and dirty energy investments. *Energy Economics*, 96, Article 105017.
- Sarkodie, S. A., Ahmed, M. Y., & Owusu, P. A. (2022). COVID-19 pandemic improves market signals of cryptocurrencies-evidence from bitcoin, bitcoin cash, Ethereum, and Litecoin. *Finance Research Letters*, 44, Article 102049.
- Sartzetakis, E. S. (2021). Green bonds as an instrument to finance low carbon transition. *Economic Change and Restructuring*, 54(3), 755–779.
- Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139–1168.
- Tiwari, A. K., Abakah, E. J. A., Gabauer, D., & Dwumfour, R. A. (2022). Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. *Global Finance Journal*, 51, Article 100692. <https://doi.org/10.1016/j.gfj.2021.100692>
- Tolliver, C., Keeley, A. R., & Managi, S. (2020). Drivers of green bond market growth: The importance of nationally determined contributions to the Paris agreement and implications for sustainability. *Journal of Cleaner Production*, 244, Article 118643. <https://doi.org/10.1016/j.jclepro.2019.118643>
- Umar, Z., Adekoya, O. B., Oliyide, J. A., & Gubareva, M. (2021). Media sentiment and short stocks performance during a systemic crisis. *International Review of Financial Analysis*, 78, Article 101896.
- Urquhart, A., & Zhang, H. (2019). Is bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*, 63, 49–57. <https://doi.org/10.1016/j.irfa.2019.02.009>
- Wan, D., Xue, R., Linnenluecke, M., Tian, J., & Shan, Y. (2021). The impact of investor attention during COVID-19 on investment in clean energy versus fossil fuel firms. *Finance Research Letters*, 43, Article 101955. <https://doi.org/10.1016/j.frl.2021.101955>
- Wu, C. H., & Lin, C. J. (2017). The impact of media coverage on investor trading behavior and stock returns. *Pacific-Basin Finance Journal*, 43, 151–172.
- Wu, S., Tong, M., Yang, Z., & Derballi, A. (2019). Does gold or bitcoin hedge economic policy uncertainty? *Finance Research Letters*, 31, 171–178. <https://doi.org/10.1016/j.frl.2019.04.001>
- Yousaf, I., Suleman, M. T., & Demirer, R. (2022). Green investments: A luxury good or a financial necessity? *Energy Economics*, 105, Article 105745. <https://doi.org/10.1016/j.eneco.2021.105745>
- Zhang, H., Hong, H., Guo, Y., & Yang, C. (2022). Information spillover effects from media coverage to the crude oil, gold, and bitcoin markets during the COVID-19 pandemic: Evidence from the time and frequency domains. *International Review of Economics and Finance*, 78, 267–285.